Projecting disaggregated household energy demand data into future scenarios: a tool to improve decision-making

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Abstract

The UK has committed to net zero carbon emissions by 2050. Reducing emissions originating from the built environment, and particularly from the domestic sector, plays a significant role in meeting this target. Buildings —and the energy infrastructure providing them— have long asset lives. Therefore, understanding the nature of their long-term energy demand is key for ensuring that any solution or strategy adopted now continues to perform effectively in the future and for preventing assets becoming stranded. Current decision support methods used to manage future energy demands address this problem mainly by analysing economically or technically favourable paths to meet predicted demands. However, predictions based on past trends are not effective when the future does not unfold linearly. In contrast, explorative scenario analysis can help to identify a range of distinct and plausible paths that the UK residential energy demand could take in the future. This allows a fuller range of potential future uncertainties faced by decision-makers to be systematically considered, maximising the chances that the decisions taken now continue to deliver their benefits regardless of the future. Effective scenario analysis requires relevant, accurate and representative data. Indeed, it is possible to project coarse level information, or aggregated data, into future scenarios to broadly characterise them. However, more specific, direct and quantitative insights about that range of identified paths could improve the usefulness of scenario-based approaches. The use of finer grain information, or disaggregated data, in scenarios could deliver such insights as well as information of the likely behaviour of distinct groups of agents. Still, this is something the futures literature lacks. This research presents a simple tool —which comprises a mathematical framework and the method to use it— developed to project disaggregated household energy demand data into future scenarios in order to explore how such data can inform decisions regarding energy demand and supply. The performance of the tool was evaluated by projecting electricity and gas demand data into the scenarios from BRE's toolkit Designing Resilient Cities (DRC). A method was developed to supplement DRC's scenarios with needed indicators conveying detailed information about households and the way they use energy. The data evolutions found with those projections can be used to improve planning the UK household energy demand, for which examples are given. Furthermore, the scope of the tool, of the method to supplement scenarios and of the new indicators are not constrained to projecting household energy demand into future scenarios: the tool is capable of projecting any kind of disaggregated data which include sufficient metadata into any scenarios which meet certain conditions (have a typical architecture, are not too disruptive and characterise the variables aimed to be projected); any scenario with a typical architecture (a general narrative plus the characteristics of a set of indicators) can be adapted with the method developed here; and the adaptation of the DRC scenarios can be seamlessly used with the original toolkit.

To you, reader,
if you dare to face the whole text.

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Abbreviations

AD	All Days
AI	Average Income
BER	Building Energy Rating
CER	Commission for Energy Regulation
DRC	Designing Resilient Cities (Lombardi et al., 2012)
Edata	Electricity trial data
EVERYTHING	all periods of time, types of day, formats, per household and per person
extended DRC	indicators supplementing DRC from Banchs-Piqué et al. (2020)
FW	Fortress World
FWp	Fortress World poor
FWr	Fortress World rich
Gdata	Gas trial data
GDP	Gross Domestic Product
GHG	Green House Gas
GSG	Global Scenarios Group
IEA	International Energy Agency
ISSDA	Irish Social Science Data Archive
MF	Market Forces
NaN	Not a Number
NSP	New Sustainability Paradigm
OECD	Organisation for Economic Co-operation and Development
PR	Policy Reform
WD	Week Days
WE	WeekEnd days

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Whilst registered as a candidate for the above degree, I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award.

The main body of this thesis comprises around 82,300 words.

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Part I

Scene-setting and context

Chapter 1

Purpose and approach

Because without a healthy Earth, there isn't a healthy anything.

— The story of stuff

1.1 Motivation

Although in today's world post-truth intoxicates the beliefs of millions of people worldwide, there is scientific consensus on human-made climate change driven by greenhouse gases (GHGs) (Cook et al., 2016). Climate change is one of the Stockholm Resilience Centre's boundaries defining a safe operating space for humanity that people have already crossed, increasing the risk of irreversible environmental changes (Rockström et al., 2009). In order to mitigate this threat, most countries are setting targets to reduce their GHG emissions. The UK has recently committed to net zero carbon emissions by 2050 (HM UK Parliament, 2019), and it recognises that the built environment plays a crucial role in achieving this target (Department of Energy and Climate Change [DECC], 2009).

In the UK, domestic consumers represented the largest share of the electricity and gas demanded in 2018 (Department for Business, Energy and Industrial Strategy [BEIS], 2019). Furthermore, it is expected that, under business as usual, the energy demand in the global building sector increases by 50% by 2050 (International Energy Agency [IEA], 2013). However, it has been estimated that to achieve the global goal of limiting the temperature rise to 2°C, the building sector has to reduce its carbon dioxide emissions by 77% compared with the 2013 baseline (IEA, 2013). Carefully planning the future of the built environment —as well as its energy-supply technologies and networks— is key in this effort, as there is a need to ensure resilient and flexible solutions that continue to perform effectively in the future.

Present research on sustainability focuses mainly on assessing the expected benefits that certain actions, technologies or regulations have immediately and in a likely long-term future based on current trends and predictions. Similarly, the approaches used by current decision support methods used to manage future energy demands are mostly based on analysing economically or technically favourable paths to meet predicted demands. Yet, development does not follow a linear path, which renders it impossible to predict the future in a consistent and reliable manner (Schwartz, 2012). Buildings have long lifespans during which their environment (social, technological, etc.) may change substantially. As a result, interventions that seem very appropriate today, even if avoiding past mistakes, may not be useful in a matter of years if this uncertainty is not taken into account during their design phase (Boyko et al., 2012).

Scenario analysis, which has been used since the 1970s (Mander et al., 2008) in various research fields, can help in this regard. Scenarios are usually designed to portray a wide range of plausible futures which could arise from the present. Scenario analysis allows us to evaluate the performance of any proposed solution in those futures. This provides information to help to improve these solutions to be resilient, *i.e.* effective in all the scenarios; or, at least, to know their weaknesses and plan accordingly (Lombardi et al., 2012; Rogers et al., 2012). In scenario analysis, future events can also be analysed to obtain a scope of the outcomes that could follow them. These kinds of analyses, however, do not usually involve the projection of any kind of data into the future scenarios.

During the construction of scenarios, it is common to project aggregated data to better characterise them. In addition, tools developed to produce scenarios have been used to project this kind of data into already constructed scenarios (Gerst et al., 2014; Tellus Institute, n.d.-b). These tools are usually complicated computer models with intricate dependencies between variables (*e.g.* Integrated Assessment Models (IAM), System Dynamics (SD) models, etc.(MEDEAS, n.d.; Rye & Jackson, 2018)) which are able to simulate the expected behaviour of some aggregated data under different assumptions for the future. However, the projection of disaggregated data into future scenarios with a simple method (no dependency between variables, simple concept and mathematics) does not exist.

This may be due to the fact that historically disaggregated data have been difficult to obtain. In particular, only a handful of sources of disaggregated household energy demand data are openly available. Authors such as Morley and Hazas (2011, p. 1 (2037)) acknowledge the difficulty to empirically gather "detailed [household] micro-level consumption data" and call for further collection and exploration of such data. However, in the last years there have been increasingly significant volumes of data generated on a daily basis, and this pace constantly accelerates (DOMO, 2018; Peters, 2012). Particularly, the growth in smart energy systems and smart grids, with their advanced metering infrastructures (smart metering devices and other end-user side measuring terminals) (Zhou et al., 2016; Zhou & Yang, 2016), promises a boost in the availability of disaggregated household energy demand data.

Therefore, the development of a simple and flexible tool to project disaggregated data of household energy demand into future scenarios holds the potential to be a useful and timely aid to improve the planning of the future built environment and its energy-supply technologies and networks. Such a tool could improve decision-making by allowing deeper consideration of the outcomes of future changes in the variables determining household energy demand and their implications. Indeed, developing and providing such a tool is the aim of this thesis.

1.2 Aims and objectives

The aim of this thesis is to provide a simple and flexible scenarios-based tool that, by projecting disaggregated household energy demand data, allows the systematic analysis of the impact that future uncertainties have on this demand. The specific objectives to achieve this aim include:

(1) Understand the state of the art of scenario planning techniques for the urban environment and identify scenarios which characterise it for UK. Identify as well the key determinants of household energy demand.

(2) Investigate how the identified scenarios can be used to model future household energy demand. Adapt or modify them if needed.

(3) Conceive and develop a simple framework to simulate the behaviour of household energy demand data when the variables determining this demand are characterised by the narrative of arbitrary future scenarios.

(4) Demonstrate the performance of the tool developed in (3) using the scenarios in (2), by testing it with disaggregated household energy demand data.

(5) Specify the tools contributions' to improve decision-making.

1.3 Problem statement

The sustainability-related literature lacks a simple and flexible tool to evaluate disaggregated household energy demand data in future scenarios.

On the one hand, future scenarios are used to create plausible spaces in which the potential implications of particular futures can be evaluated systematically. This helps the user to think about the future in a structured way, based on a set of assumptions that may have gone unseen otherwise. However, it is not common to project data into scenarios. And, when this is done, it is aggregated data projected using complex computer models.

On the other hand, traditional decision support tools and methods used to manage future energy demands, usually only account for a business as usual scenario, sometimes with few variations around it. Such an approach is of no use when trends change. And, although some instances of tools specifically designed to obtain projections for a particular set of economic scenarios exist, these are tools designed or tailored to specific probable economic scenarios; *i.e.* used in a narrow range of scenarios and not usable with any other scenario.

A simple and flexible tool to project disaggregated household energy demand data would fill the gap between these two fields and be valuable to improve the decision-making process in the planning for the future infrastructure related to the use of energy in the housing sector. This is particularly important because buildings have a long lifespan. In addition, such a tool would be a timely addition as the data related to household energy demand are likely to significantly increase with the wide adoption of advanced metering infrastructures.

In this thesis, secondary disaggregated energy demand data are projected into the previously adapted scenarios from Designing Resilient Cities (DRC) (Lombardi et al., 2012) by means of a simple tool conceived to that end. The different projections into each scenario are subsequently aggregated to obtain a general picture of how the data behave in the scenario and these outcomes are analysed to discuss how the tool can improve decision-making. In addition both, the adaptation of the scenarios as well as the tool, can be used independently. The adaptation of the DRC scenarios give DRC deeper detail about households and the way they use energy. The tool —which comprises a mathematical framework and the method to use it— can project any kind of disaggregated data which fulfils some criteria (see Chapter 5) into any kind of scenario related to the data which has a fitting architecture.

1.4 Path followed

In order to fulfil the aim of the thesis, the path followed was the one implied by the objectives.

The first step was to review the literature about building energy and, in particular, that about determinants of the household energy demand. This review enabled the location of the data (with metadata) which would afterwards be projected. The literature about future scenarios was reviewed as well, focussing on that related to urban UK.

Using the knowledge gained with the literature reviews as basis, an iterative process to define and characterise the main determinants of household energy demand which were not already characterised in DRC was carried out.

With this process a deeper knowledge of the architecture of scenarios was gained, which facilitated the formulation of the mathematical framework to project disaggregated data into future scenarios.

Once the tool was prepared, and with the information contained in the metadata, the variables that could be projected were defined and the factors needed to project them derived. The software 'MATLAB' was first used to obtain projections for all the variables and subsequently to aggregate them. All this process and its analysis led to the conclusions presented at the end of this document.

1.5 Thesis structure

The structure of this thesis broadly follows the conventional *Introduction - Methods - Results - Discussion and Conclusions - Appendices* structure, which is marked by its five parts. However, a large portion of the outcomes provided are beyond the "results" part as such (Part III - *Projecting household energy data into future scenarios*). The method developed to derive new indicators, the tool to project disaggregated data and the indicators supplementing DRC which are provided here are important outcomes as well. Therefore, the Discussion chapter includes a review of these outcomes, Section 8.4. This compilation, at the same time, makes the consultation of these contributions easier as it makes it unnecessary for the user to go back and forth the thesis searching for the different outcomes.

In addition to this document, the thesis comes with some electronic data. An explanation of the files enclosed there can be found in Appendix D.

The depth in the numbering of figures and tables reaches the subsection level. Although this may be disturbing at times, this is because a very large number of tables and figures are presented in the different subsections of Section 6.5 - *Development and projections of variables*, and they need to be easily attributed to the corresponding subsection.

Chapter 2

Background and literature review

Some dream to escape reality, some dream to change reality forever.

— Sōichirō Honda

2.1 Energy demand in households

Building physics is complex, with many entangled factors playing a role in determining the energy the building will consume for keeping a comfortable temperature, air quality and light levels. Such factors include orientation, percentage and position of the glazing as well as their shadowing, level of insulation, thermal mass, type of ventilation, thermal bridges, etc. (Thomas, 2006).

On top of that complexity, there is the problem of the gap between the performance a building actually shows when constructed and the performance it was designed to have (Shi et al., 2019). A very comprehensive report of the now extinct Zero Carbon Hub summarises the evidences and assessments they made (Zero Carbon Hub [ZCH], 2014). It also provides a structured review of how and where the Performance Gap occurs in the process of building a house. The key factors contributing to this Performance Gap are: (1) the lack of education and skills of the workers involved in designing and constructing a building; (2) a lack of understanding of the impact that decisions taken in all the stages of construction have on the energy performance of the building; (3) a lack of attention to detail in all the phases of building construction from the design to the actual construction or the procurement; and (4) a limited willingness to deliver an efficient building (ZCH, 2014). One problem making this situation more difficult to solve is that there are no reliable methods to easily test the energy performance of a building or dwelling in a reasonably short time.

In Europe it is compulsory to label all existing dwellings with an energy performance certificate. These certificates label the theoretical gas and electricity consumption of the dwelling based on its physical characteristics, heating, ventilation and cooling systems, and standard use characteristics. These labels, however, have been shown to not convey accurate information of actual energy consumption (Majcen et al., 2013; Sunikka-Blank & Galvin, 2012). It is shown that, in general, dwellings with low energy labels consume much less energy than predicted and energy-efficient dwellings consume more than predicted.

There are efforts to improve this situation. Initiatives like the *Assured Performance Process* from the National Energy Foundation (National Energy Foundation, n.d.) are designed to mitigate this performance gap by offering constructors know-how, expertise, and accompaniment in all the stages of construction, making sure designs are implemented thoroughly on site. Building Information Modelling promises to help improve designing and delivering buildings that perform as designed. It provides better communication and participation of the different stakeholders in all stages of building life cycle (Tuohy & Murphy, 2015).

Standards like the Passivhaus concept try to decrease the energy consumed by households. The Passivhaus standard is spreading rapidly in German-speaking countries, but it is also starting to be used in the UK (according to the Passivhaus Trust, in August 2019 there were 1290 certified units in UK, and over 65,000 buildings have been designed, built and tested to this standard worldwide (Passivhaus Trust, n.d.)). This standard is based on a holistic approach to improve the envelope of the building to decrease the need for heating, therefore reducing its energy consumption (Feist et al., 2005). This and other approaches to reduce the energy needed to heat a dwelling are being developed and improved.

However, these improved building standards, together with higher internal gains of temperature (*e.g.* due to increased amounts appliances used), the prediction of an increase of extreme weather events and other context circumstances, introduce a problem which was previously almost non-existent in these countries: the overheating of the dwellings (Dengel et al., 2016; ZCH, 2015). The previously mentioned Zero Carbon Hub estimated that potentially up to 20% of the 2016 stock of houses in England could overheat (ZCH, 2015), and produced extensive documentation on understanding that problem and tackling it; they can be found in section "Overheating" of their on-line library (ZCH, n.d.).

In terms of trying to understand the key determinants of the energy consumed in buildings, they are usually classified in building factors, socio-economic factors and occupants' behaviour. Occupants' behaviour is, however, very difficult to measure, since the perceptions and values of consumers do not usually correspond to their energy use (Gram-Hanssen, 2014; Huebner, Hamilton, Chalabi, et al., 2015).

The building factors which most often appear in the literature are the type of building, its energy efficiency (wall type, glazing, insulation, lighting...), the size of the dwelling (total floor area, number of floors, number of rooms or bedrooms...), the age of the building, the presence or not of a conservatory, and presence or not of mechanical ventilation or cooling systems (Bhattacharjee & Reichard, 2011; Huebner, Hamilton, Chalabi, et al., 2015; Huebner et al., 2016; Jones et al., 2015; Jones & Lomas, 2015).

The main socio-economic factors which influence the energy demand of households are their size and its age distribution (particularly the presence of teenagers and elderly people), the level of education and knowledge of their members (particularly of the household reference person), their income (disposable income, social class, employment status...), the tenure type in which they occupy the dwelling (ownership, rent including or not additional costs, rent free...), and the time occupants spend at home (Bhattacharjee & Reichard, 2011; Huebner, Hamilton, Chalabi, et al., 2015; Huebner et al., 2016; Jones et al., 2015; Jones & Lomas, 2015).

Other factors that also play a role in determining the energy a building consumes are the climate and particularly the micro-climate of the building, the energy price, its use of renewable energy and the affordability of energy efficient equipment (Bhattacharjee & Reichard, 2011; Jones et al., 2015; Kavousian et al., 2015).

Building factors alone are shown to explain at least 39% of the variability of energy use in buildings (Guerra-Santin et al., 2009; Huebner, Hamilton, Chalabi, et al., 2015; Huebner, Hamilton, Shipworth, et al., 2015; Sonderegger, 1978). For example, although larger dwellings tend to use more energy, there are still extensive differences in energy consumption between similar dwellings (Wright, 2008). Huebner, Hamilton, Chalabi, et al. (2015) have, in addition, shown that when taking into account building factors together with socio-economic factors —which by themselves explain 24% of the variability— and measurable behavioural factors in a combined model, they can explain only 44% of the variability.

This result carries two major implications. The first one is that the percentage of variability in the energy use in buildings explained by several factors studied together is significantly lower than the sum of the variabilities each factor explains when studied in isolation. This corroborates that the different factors are in some way correlated, showing that the batch of factors which play a role in the energy demand of buildings is intricate and complex.

The second implication is that this leaves more than 50% of the variability in domestic energy consumption unexplained (Huebner, Hamilton, Chalabi, et al., 2015; Huebner, Hamilton, Shipworth, et al., 2015). Indeed, a crucial factor in the energy that households consume is the behaviour of the inhabitants of the dwellings (Firth et al., 2008; Lindberg et al., 2008; Perry & Bessant, 2014) which, as previously mentioned, is difficult to measure. Heating (gas) consumption is mainly influenced by the occupancy of the property (who, how long, etc.) and temperature management (Fell & King, 2012; Weber et al., 2017), with ventilation behaviour having a major impact as well (Weber et al., 2017). Variables influenced by people have the strongest predictive power to explain English household non-heating electricity consumption (Huebner et al., 2016). This consumption is determined mainly by the type and number of electrical appliances and the use that the occupants make of them (Firth et al., 2008; Huebner et al., 2016; Jones et al., 2015). However, more detailed knowledge on how occupants influence the final energy consumption of buildings is needed in order to decrease it; in particular to adapt the buildings and energy-efficient technologies to user practices and to be able to persuade consumers to lower their energy consumption (Gram-Hanssen, 2014).

Behavioural economics shows that trying to influence human behaviour to a particular end is a very challenging endeavour. This is, at the same time, an opportunity and a challenge, since the same features of human behaviour can help reduce energy consumption or make the change more difficult. Also, human behaviour is very complex with many factors acting simultaneously, leading to a particular behaviour in a particular point in time. For example, humans tend to follow the behaviour of our peers (Bikhchandani et al., 1992), tend to rationalise our behaviours (*e.g.* our actions may create our preferences (Ariely & Norton, 2008), or when faced with complex decisions we tend to choose the default option (Davidai et al., 2012).

There are various ways to study how the attitudes of the occupants influence the energy consumed in dwellings, the causes of these attitudes, and how to influence them (Fell & King, 2012; Gram-Hanssen, 2014; Guo et al., 2018; Perry & Bessant, 2014; Weber et al., 2017). Very well designed behavioural strategies may help decrease the energy households consume. However, studies repeatedly show that it is very difficult to change the behaviour of a core group of customers (which tends to be the largest single group) in energy efficiency projects (Perry & Bessant, 2014). This is the main conclusion reached by the first report of the project Solent Achieving Value from Efficiency (an Ofgem funded project that evaluates the potential for domestic customers in the Solent region of UK to actively participate in improving the resilience of electricity distribution networks, (SAVE, n.d.)). Although this is not a peer-reviewed report, it is a thorough review of customer engagement studies with the following findings: (1) there is a need to segment customers; (2) the customers need to understand how they can reduce energy consumption; (3) the messages have to be delivered by trustworthy and authoritative voices; (4) financial incentives can be effective but not long term; (5) like-to-like comparisons are effective motivators; (6) preference to use opt-out designs if possible; (7) creative and frequent information motivates users; (8) there must be a balance using negative concepts and making customers feel good; (9) setting goals can be effective; and (10) it is important to lead by example.

In terms of where is the most energy consumed, the energy used for space heating is, by far, the largest slice of the energy used in UK households. Together with water heating —the second largest slice— they accounted for around 80% of the energy used in UK households in 2011 (around 60% and 20% respectively) (Palmer & Cooper, 2013). Therefore, the energy source used for heating has a major impact on the total consumption of the corresponding source. The vast majority of homes in the UK (more than 80%) use gas for heating purposes. Most of the non-gas energy used for heating, as well as virtually all the energy used for non-heating-related purposes in UK households, is electricity. Therefore, these two sources of energy account for almost all the energy used in UK households.

The efforts to close the performance gap, better building standards and new regulations mandating and promoting them promise to decrease the energy consumed in new buildings. However, there is a large stock of already constructed residences that need to be addressed; it is estimated that two-thirds of the dwellings likely to be in use in the UK in 2050 were already constructed in 2005 (Boardman et al., 2005). Therefore, significantly reducing the energy consumption of domestic buildings means that the existing stock needs to be refurbished.

Refurbishment in the UK has a problem with public confidence due to a history of poor quality installations. Bonfield (2016) tackles this problem designing an environment to guarantee high quality refurbishment and get back public trust. The solution proposed in the review is to create a *Quality Mark* which obligates the companies in the sector wishing to use it to adhere to three key elements: (1) a Consumer Charter to ensure consumers receive excellent service, (2) a Code of Conduct the requirements of which have to be met or exceeded, and (3) Codes of Practice to minimise the risk of poor quality installations (Bonfield, 2016). It is calculated that with only the insulation of lofts and cavity walls, the consumption of fuel for space heating could be reduced by between 10% and 17% in England (Hong et al., 2006).

Some recommendations to decrease household electricity demand arising from one of the biggest measurement campaigns ever made, in Sweden, are limiting the power consumption of appliances on standby to 0.5 W, encouraging cutting the electrical supply of the appliances instead of leaving them in standby mode, and accelerating stricter consumption norms to make class A appliances (according to the European Union energy label) become the standard (Zimmermann, 2009).

Under business as usual, the expected energy demand in the global building sector will increase by 50% by 2050 (IEA, 2013). In the coming years, the increasing uptake of electric vehicles will presumably increase the stress in the electric network and transfer significant amounts of the energy used in transport to household electricity demand (Catapult, 2018).

Managing energy demand, in particular that demanded in the domestic sector, is important as the future of the world depends on the decisions taken today. A range of tools and decision support methods are currently used to manage the energy systems. The next section briefly describes them.

2.2 Energy demand decision support methods

Energy planning is key to help guide the future of domestic energy systems. There exist a large range of tools, models and methods to support decision-makers to formulate strategies and recommend energy policies. As energy planning is a huge domain, different approaches may have different aims, which typically translates into different strengths and weaknesses.

Modelling and analysing the energy sector and its possible futures is essential for energy planning. There exists a plethora of energy models utilized both in academia and in policy (Bhattacharyya & Timilsina, 2009, 2010; Hall & Buckley, 2016) that are constantly evolving, hybridizing and subdividing (Bhattacharyya & Timilsina, 2009). Most of these models attempt to answer questions such as: how can the future energy demand be covered without nuclear energy, with such percentage of renewables, or without exceeding a given CO_2 budget? *e.g* (Zafeiratou & Spataru, 2014). Or, what would the future energy system look like (generation, cost of energy, etc.) if such incentives, technologies, or both were adopted? *e.g* (van Vuuren et al., 2009). These models typically either employ forecasts and trends to simulate, based on hypotheses, the future of the energy system, or optimise the lowest cost configuration of the system to reach a desired target (*e.g.* mix of technologies or allocation of production factors) based on a set of assumptions and for a given country or region (Bhattacharyya & Timilsina, 2009; Koppelaar et al., 2016; van Vuuren et al., 2009).

Energy models can be classified following different criteria. The criteria most often used are to describe the model's analytical approach (mostly top-down, bottom-up or hybrid), the method they employ (*e.g.* simulation, optimisation —including or not equilibrium models—, econometric...), their mathematical approach (programming techniques used), or a combination of these (da Silva, 2017; Hall & Buckley, 2016; Koppelaar et al., 2016; Lee, 2016).

Following, a very brief description of the main analytical approaches and methodologies used in energy models is given. Reviews comparing, classifying and describing models and/or describing these approaches and methodologies exist elsewhere. For an in-depth comparison of the most important energy models see the appendix of Bhattacharyya and Timilsina (2009), which presents a detailed comparison of selected models. Hall and Buckley (2016) propose a classification schema to make the "model landscape more accessible and perspicuous", and compare 22 energy models used in the UK context with the schema. For a review of energy models under broad categories see Suganthi and Samuel (2012) or Pfenninger et al. (2014), for models predicting building energy use see Zhao and Magoulès (2012), for electricity models see Koppelaar et al. (2016), or for community energy planning models see Huang et al. (2015).

Top-down The top-down analytical approach focuses on market interactions within the whole economy and uses historically derived variables to analyse aggregated behaviours. The macro-economic design of models using this approach makes them useful for studying economy-wide responses to policies. However, they tend not to be flexible, assume historic behaviour to be relevant for the future, usually cannot capture policies which are not price based, and have little technological detail (Bhattacharyya & Timilsina, 2009; Hall & Buckley, 2016; van Vuuren et al., 2009).

Bottom-up The bottom-up analytical approach focuses on how distinct energy technologies can be used and substituted, and their relative costs. Models using this approach are more detailed and flexible, allow evaluation of a wide range of policy options and are useful to study specific technical opportunities. However, they do not account for macro-economic feedbacks between the energy and other economic sectors, are usually inconsistent with the macro-economic performance of the country, and are not able to capture price based policy analysis (Bhattacharyya & Timilsina, 2009; Hall & Buckley, 2016; van Vuuren et al., 2009).

Hybrid The hybrid analytical approach links a macro-economic approach with some technological detail. Hybrid models can be a coupling of exiting models using top-down and bottom-up approaches (soft-linked) or a separate model which integrates features of both approaches (hard-linked) (Hall & Buckley, 2016; van Vuuren et al., 2009).

Optimisation The optimisation method tries to find the least cost solution or system configuration (*e.g.* preferred mix of technologies) given certain constraints and targets. The **equilibrium** method compartmentalizes optimization (supply, demand...) and finds the market clearing equilibrium. These methods can identify the theoretical least-cost solution and cover the entire energy system or only part of it. However, they assume that real world decisions are always made on the basis of lowering cost, and they are typically complex and data intensive. (Bhattacharyya & Timilsina, 2009; Hall & Buckley, 2016; Koppelaar et al., 2016; Pfenninger et al., 2014; van Vuuren et al., 2009)

Simulation The simulation method may describe the energy system based on a set of rules and attempt to reproduce its operation, or simulate the interactions between its agents and higher system components. The resulting forecasts can provide answers to 'what-if?' questions. However, models using this method do not necessarily lead to full equilibrium (which can lead to apparent negative costs) and are often complex and opaque due to their assumptions about behavioural factors (Bhattacharyya & Timilsina, 2009; Hall & Buckley, 2016; Koppelaar et al., 2016; van Vuuren et al., 2009).

As it can be seen with the hybrid analytical approach, the line between different approaches or methods can be blurred. Distinct models may be soft-linked to combine their advantages or, sometimes, approaches and/or methods can be hard-linked in new, more advanced, models.

A typical feature of energy models is that they are opaque (mechanics of the model not described in detail) and inaccessible (analyses not reproducible because code and/or accompanying data not publicly available), while at the same time sensible to their baseline assumptions and inner workings. There is also the common perception that the more complex a model is and the more input data it needs, the more accurate results it produces —in reality, if prediction is the goal, simple energy models are often no worse than complex ones (Pfenninger et al., 2014)—. All this typically makes the models difficult to evaluate and their results difficult to be reproduced. These are important issues, particularly when insight obtained with models is used for public policy, since public policy should be able to undergo independent scrutiny (Bhattacharyya & Timilsina, 2009; Pfenninger et al., 2014).

These problems greatly difficult the choice of which model to use for a given purpose and environment, and may lead to the incorrect application of the model. When a model is incorrectly applied or its assumptions not well understood, the interpretation of their outputs may easily be incorrect (Bhattacharyya & Timilsina, 2009; Pfenninger et al., 2014). Although part of these issues could be easily overcome by publicly releasing data and models, in practice doing it is not straight forward; modellers have limited time and resources (which they prefer to invest in improving the model), and energy systems models often contain proprietary knowledge and commercial data (Pfenninger et al., 2014).

Energy models mostly focus in producing probable or desired scenarios, and/or the path to reach them (Pfenninger et al., 2014). They typically find factors to closely fit past data and use them to produce their forecasts (Bhattacharyya & Timilsina, 2009). In addition, they sometimes produce small variations around the reference forecast as well to broaden the analysis (Lee, 2016; Suganthi & Samuel, 2012). Energy models usually link energy, economy and environment (Suganthi & Samuel, 2012) but tend not to take into account interactions between government, firms and society (Koppelaar et al., 2016).

Most non-bottom-up national or global models are purpose-built and rigid. They tend to be very appropriate for the purpose they were designed to accomplish but incapable of being used in different environments. And they require specialised skills to be operated, making them inaccessible to wider users (Bhattacharyya & Timilsina, 2009). In contrast, bottom-up models are more flexible and, therefore, more widely used. They rely on the systematic development of consistent scenarios and use data disaggregated by sectors (Bhattacharyya & Timilsina, 2009; Suganthi & Samuel, 2012).

The energy model which is, by far, the most widely cited and used is MARKAL —MARKet ALlocation— and its variants (*e.g.* UK MARKAL, SAGE, TIMES). MARKAL is a general purpose bottom-up optimisation model which covers the entire energy system and was developed by the International Energy Agency. It can be adapted to model energy systems ranging from regional to global levels over several decades, and can analyse the environmental effects of the model. The original MARKAL model has evolved in distinct ways to adapt it to several purposes and contexts. Some of the models comprising the MARKAL family are examples of hybrid models, linking MARKAL with top-down models; *e.g.* MARKAL-MACRO (Bhattacharyya & Timilsina, 2009; Hall & Buckley, 2016; Pfenninger et al., 2014; Suganthi & Samuel, 2012).

Other models particularly worth mentioning are MESSAGE and LEAP. MESSAGE —Model for Energy Supply Strategy Alternatives and their General Environmental Impact—, is also a bottom-up optimisation model with very similar purposes to MARKAL but a shorter time horizon. It also has a family of evolved models aimed at fulfilling different purposes, and was developed by the International Institute for Applied Systems Analysis. LEAP —Long-range Energy Alternatives Planning system—, is a flexible hybrid simulation model which covers the entire energy system following an accounting framework. It was developed by the Stockholm Environment Institute and it is used for forecasting and modelling energy needs ranging from city to global level (Bhattacharyya & Timilsina, 2009; Hall & Buckley, 2016; Pfenninger et al., 2014; Suganthi & Samuel, 2012; van Vuuren et al., 2009).

Most of the effort in energy systems modelling is usually directed to produce probable scenarios in order to analyse them, as this analysis is essential for energy policy making (Pfenninger et al., 2014; Spataru et al., 2015). However, there exists another paradigm to generate energy scenarios to allow energy systems analyses, the use of qualitative and/or mixed methods scenarios. This approach is less referenced in the energy modelling literature but can produce equally useful scenarios. The methods used can range from a combination of qualitative and quantitative approaches to pure qualitative methods. These kind of scenarios avoid the greatest weaknesses of large-scale energy systems models, their complexity and opacity, by providing greater simplicity and transparency (Pfenninger et al., 2014).

One example that provides simple but quantitative scenarios is the set of pathways to 2050 of the UK Department for Energy and Climate Change (DECC, 2010). It portrays a range of possible changes each sector of the economy could undertake. For each sector, four different future trajectories are developed, ranging from very little effort exercised to reduce emissions or save energy, to extremely ambitious changes pushing towards current technical limits. These are transparent and accessible (through spreadsheets and a web application) by design. Although the report describes six scenarios (combinations of trajectories with different levels of effort for each sector), a web application allows the users to develop their own combinations to perform their own analyses (DECC, 2010; Pfenninger et al., 2014).

Energy demands projected by energy models often deviate from actual demands. This may be due to limitations in the structure of the model or inappropriate assumptions (Bhattacharyya & Timilsina, 2009), but also to the impossibility to forecast a changing future based on past trends. This is a clear limitation of forecasting models which, since in the long run future cannot be predicted (Schwartz, 2012), is virtually impossible to avoid with this approach. In contrast, qualitative and mixed-methods scenarios can easily produce explorative scenarios. Explorative scenario analysis attempts to define a range of plausible paths that the energy demand could take without prioritising them by likelihood. This broadens the space of study from one forecast (or a narrow range of probable futures) to a wider range of possibilities while, at the same time, limiting it to only plausible paths; *i.e.* leaving out possibilities which are not plausible. In this way, a wider range of futures can be analysed with a limited set of scenarios, and the limitations associated to forecasting can be overcome.

In addition to models and scenarios, decision-makers also have at their disposal general guidelines, assessment questionnaires and other methods and tools in general that may or may not be specificity aimed at managing the future energy demand but that can aid them in that effort, or in assessing what could be improved in the current system and how. One relevant example of general guidelines is *The Green Book* by HM Treasury (2018). It provides guidance and methods on how to appraise and evaluate policies, projects and programmes to support the government's decision making, as well as recommended tools for developing its options and standard values to be used across government (HM Treasury, 2018). Assessment questionnaires can be focussed on civil engineering like CEEQUAL (BRE, n.d.), or be holistic like the *Economy for the Common Good* Balance Sheet (Blachfellner et al., 2017). The thesis by Lee (2016) offers an example of a different tool that can be used in the energy systems decision-making process; it provides a procedure for energy planning in the context of developing countries.

As just seen, the range of tools, models and methods directly or directly aimed at managing future energy demand that decision makers can use as support to formulate strategies and recommend energy policies is extensive. However, the tendency of these tools to use forecasts and variations around them involve limitations. History does not follow a simple linear path, and buildings and their energy systems have long asset lives. In consequence, solutions, regulations and plans affecting the energy demand in households may stop delivering their advantages during the lifespans of these assets —even if they thoroughly account for past trends and avoid past mistakes—. This would lead to these assets growing stranded, resulting in large amounts of effort and resources being lost. For this reason, it is key to consider future uncertainty when designing such interventions. An analysis of the determinants of the energy demand in households with explorative future scenarios would identify a range of distinct plausible paths that this demand could take in the future, thus reducing the uncertainty faced when designing interventions, plans or regulations affecting it.

2.3 Future scenarios

Almost everyone has an idea of what a future scenario is, at least broadly. The concept 'scenario' is used in general media (*e.g.* (BBC, n.d.)), companies (*e.g.* (Accounting for sustainability, 2020)), governments (*e.g.* (Swain & Steenmans, 2016)) and even in daily life (*e.g.* ("Is it better to hope for the best or prepare for the worst?", n.d.)). And, since some months, governments and scientists use scenarios to map possible ways out of the COVID-19 pandemic (*e.g.* (Neher et al., 2020; Snow, 2020)).

Although scenarios appear in our daily life, it is important to define them to clarify what they are and their applications. The Organisation for Economic Co-operation and Development (OECD) defines future scenarios as "carefully constructed snapshots of the future and the possible ways a sector might develop". Then, it immediately continues by explaining their use: "Scenarios help focus thinking on the most important factors driving change in any particular field. By considering the complex interactions between these factors, we can improve our understanding of how change works, and what we can do to guide it" (Organisation for Economic Co-operation and Development [OECD], n.d.). This is a good indication that the importance of future scenarios heavily lays on their use rather than on the formalities of what their exact definition or form are.

Precisely because almost everyone has an idea of what scenarios are, it is also critical to emphasise what scenarios are not in order to dissipate any misconception. Scenarios are not forecasts or predictions; neither are they projections or recommendations (Hunt et al., 2012b; van der Heijden, 1996) and they explicitly do not include trend analysis (Hunt et al., 2012b). Scenarios present distinct futures and they do it without any value judgement about their likelihood or whether they are more or less preferable. However, scenarios convert the danger of self-fulfilling prophecies into a strength; anticipating a range of futures enables us to produce roadmaps and align decisions to choose the desired one (Shala, 2018).

In order for future scenarios to emerge as a useful tool, a long history of evolution in human thought was needed. Starting with remarkable progress in the way humans look into the future and understand the cause and effect of events, and culminating in the development of complex modelling of the future where the response to unanticipated events gained importance (Shala, 2018).

> "Roughly summarized, the definition of the future has shifted over the course of history from being a part of divine eternity to a sphere of progress and perfectibility, and finally to a field of active planning and change" (Shala, 2018, p. 11).

This evolution in the concept of future facilitated, in the modern times, the emergence of a new field of study, futures research. The first paradigm in this field was focussed in forecasting, *i.e.* predicting, planning and controlling (Shala, 2018; van der Heijden, 1996). However, this paradigm was put into question by two main pessimistic events (Son, 2015): (1) the well-known report *The limits to growth* (Meadows et al., 1972), which concludes that unlimited economic and population growth will cause economic collapse and have negative environmental impacts; and (2) the shock generated by the 1973 oil crisis. These events convulsed the futures community and favoured an alternative approach, analysing multiple futures (Shala, 2018). Futures scenarios had already been used for some years, *e.g.* three oil related scenarios were used in 1967 to describe the possible futures in the year 2000 (Kahn & Wiener, 1967; as cited in Hunt et al., 2012b). Yet, since these events, the adoption of future scenarios for the futures community has been wide.

There exist scenarios of different forms, with different features depending on the use to which they are put. Some model specific outcomes and consequences from current actions or propose strategies to be taken under distinct situations. These may not need structure or detailed narrative. For example, the different emissions scenarios that the

Intergovernmental Panel on Climate Change developed for each of their storylines (Intergovernmental Panel on Climate Change [IPCC], 2000), the energy-transition models reviewed by Rye and Jackson (2018) or the mosquito scenarios which guide the strategy for mosquito control programmes proposed by Martinou et al. (2020). The scenarios used within the futures studies, in contrast, are typically defined by narratives and explore distinct plausible economic, social, cultural, institutional, political, security, technological and/or environmental futures that could arise from the present.

These scenarios are plausible and relevant built stories of the future that challenge mental models for how we live now (Hunt et al., 2012b) and account for critical uncertainties (Raskin, 2005). They are tools for thinking about the future (Foresight Energy and Natural Environment Panel, 2002) and are usually "told in words and numbers" (Raskin, 2005), *i.e.* a narrative storyline with quantitative and qualitative indicators that describe key future changes (Hunt et al., 2012b). When they are carefully built and coherent, their events unfold governed by their narrative and logical plot (Hunt et al., 2012b; Schwartz, 2012). However, it has to be pointed out that there can be multiple sets of actions leading to the same future (Hunt et al., 2012b).

One of the key features of scenarios is that, although they introduce multiple futures, they simplify the analysis of the future instead of making it more complicated. This may seem paradoxical; however, their internal logic acts as a complexity-reduction device: it segments complexity into distinct concrete, causally coherent narratives (Aligica, 2005), pushing uncertainty across distinct futures rather than within a single one (Schoemaker, 1991). They are a simple to interpret and elegant solution to the problem of how to construct models that put order in complex systems with high uncertainty (Aligica, 2005). This is adaptive to the human mind, which can only handle a limited amount of complexity (Schwenk, 1984; as cited in Aligica, 2005).

By portraying distinct and plausible futures and stimulating a rational evaluation of issues, future scenarios can be effective devices to deal with human biases like overconfidence, availability and anchoring; especially for those individuals involved in their development (Aligica, 2005). Moreover, their internal logic provides the grounds for further inquiry and the integration of new information (Schoemaker, 1991), as well as enabling the understanding of consequences which could easily be overlooked in abstract discussions and analysis (Kahn & Wiener, 1967; as cited in Aligica, 2005).

Future scenarios help us to consider, question and analyse how the world might unfold. With this, they help us prepare and adapt to changing aspects of our environment (Schwartz, 2012), and to ask 'what-if?' questions about the future (Rogers et al., 2012). Scenarios are a good means of communication between scientists and policy-makers and they help sorting out urgent policy issues (Hunt et al., 2012b). In addition, they liberate planning from the traditional predict and control approach (van der Heijden, 1996), and help reveal where alternative thinking may help policy and practice (Banchs-Piqué et al., 2020). It is in general recommended to use at least two scenarios —as one is too easily mistaken for a forecast— and a maximum of four. This range eases the engagement of the users while allowing a deep and rigorous analysis (Hunt et al., 2012a).

Although a number of different groups have produced scenarios, future scenarios tend to follow four similar assumptions and show four more or less explicit commonalities (Hunt et al., 2012b). The shared assumptions are (Hunt et al., 2012b): (1) the future is significantly influenced by human action; (2) although the future cannot be foreseen, exploring it can inform present decisions; (3) there are many possible futures and scenarios map some of them; and (4) rational analysis as well as subjective judgement are needed to develop them.

And the commonalities they show are (Hunt et al., 2012b): (1) some boundaries related to their theme, timeline and space; (2) some means of quantifying or qualifying the evolution toward the distinct futures; (3) a set of plausible narratives describing the future; and (4) some indicators which quantify or qualify the narrative within the boundaries.

There exist two main types of scenarios, normative and explorative. Normative scenarios usually involve some business-as-usual scenario and/or variations around it (van Vuuren et al., 2012). These scenarios are commonly used to identify preferable alternative futures (such studies are anticipatory or prescriptive —they may portray roadmaps for the future to help define which one to implement—) or to formulate response strategies to specific problems.

Explorative scenarios, on the other hand, portray a broad range of plausible futures. They may extend to the extremes of plausibility to offer a complete view of what is plausible (Gallopín & Raskin, 2002; Hunt et al., 2012a). These scenarios can be used to test the robustness or resilience of different options under future uncertainties, *i.e.* that they will continue to deliver their intended benefits for the duration of their lifespan (Boyko et al., 2012; Hunt et al., 2012b). These scenarios usually include radical shifts in social and cultural conditions which we unconsciously assume to be fixed (Hunt et al., 2012b).

In a thorough review of the futures literature from 1997 to 2011, Hunt et al. (2012b) identify four key steps vital to develop scenarios. These steps and a short explanation of what they entail follow:

(1) Identify the 'big strategic question(s)'. This is a key generic step that is widely used. Typically, one or two questions are adopted, although the adoption of more questions is not uncommon.

(2) Identify primary drivers of change. To attempt to understand the future, it is necessary to determine the driving forces that are at play. At global levels these can be commonly represented under the acronym STEEPO (Social, Technological, Economic, Environmental, Political, Organisational) (South East England Development Agency, 2003; as cited in Hunt et al., 2012b). The list of drivers has to be adapted to the purpose the scenario aims to fulfil.

(3) Identify critical uncertainties. Here the key uncertainties driving the scenario are identified (leaving aside what is relatively certain). This process helps to identify the drivers which are most influential to perform a deeper analysis on them.

(4) Derive the scenarios themselves. There are a variety of methods to derive the scenarios when the previous steps are fulfilled. Each method provides different lenses through which the future can be viewed. Therefore, it is common for recent studies to adopt a combination of these approaches. Regardless of the approach adopted, scenarios must address the questions identified in step (1). They should also be plausible, robust, divergent and challenging in order to offer credibility and be useful (Ratcliffe & Sirr, 2003). Hunt et al. (2012b) found seven methodologies that have been adopted in the literature; these are: (a) the 'Two critical dimensions of uncertainty' and (b) the 'Three (or more) critical dimensions of uncertainty', which use the 'axes of uncertainty' to map the scenarios space; (c) 'One (or more) key drivers'; (d) 'The three horizons analysis'; (e) 'The futures wheel'; (f) 'The ethnographic futures framework (EFF)'; and (g) 'Shaping actors shaping factors'. The two main methods used to derive scenarios in the period reviewed are the axes of uncertainty and the key drivers —a brief explanation of these methods follow—. For deeper insights on each of these methods (Hunt et al., 2012b) can be consulted.

The axes of uncertainty method use the previously derived uncertainties as bases. It usually requires two key uncertainties which determine the x and y axes forming four distinct quadrants. These quadrants map the main properties of four scenarios, see Figure 2.3.0.1 for an example of the two axes of uncertainty used by (EA, 2010). Based on these main properties and the steps previously mentioned, the characteristics of the scenario can be developed. This approach should be used to produce scenarios which are mutually exclusive and contrasting, and for outcomes that are high impact and highly uncertain. While the use of two axis of uncertainty is very simple, it runs the risk of missing important future scenarios. Therefore, in some cases more than two axes of uncertainty have been used following the same principle. This method is particularly suited for an in depth research of the impact of significant events.

The key drivers method explores the ramifications and extensions of one central driving force and the scenarios are typically derived by expert assessment (Hunt et al., 2012b). This method has the advantage of not being constrained to a single set of axes. It allows the generation of both, moderate and extreme scenarios by accordingly adjusting the assumptions used to produce them. This includes what in the scenarios literature is referred to as 'wild cards', events which are high impact but low probability. The key drivers approach is particularly suited when a broad analysis is required.

A significant number of the scenarios used in the recent futures literature fall within one of three world end-states proposed by the Global Scenarios Group (GSG) in 1997: (1) Conventional Worlds, (2) Barbarisations and (3) Great Transitions (Hunt et al., 2012a, 2012b). These three world types are "sufficiently diverse, distinct, clearly defined, well-

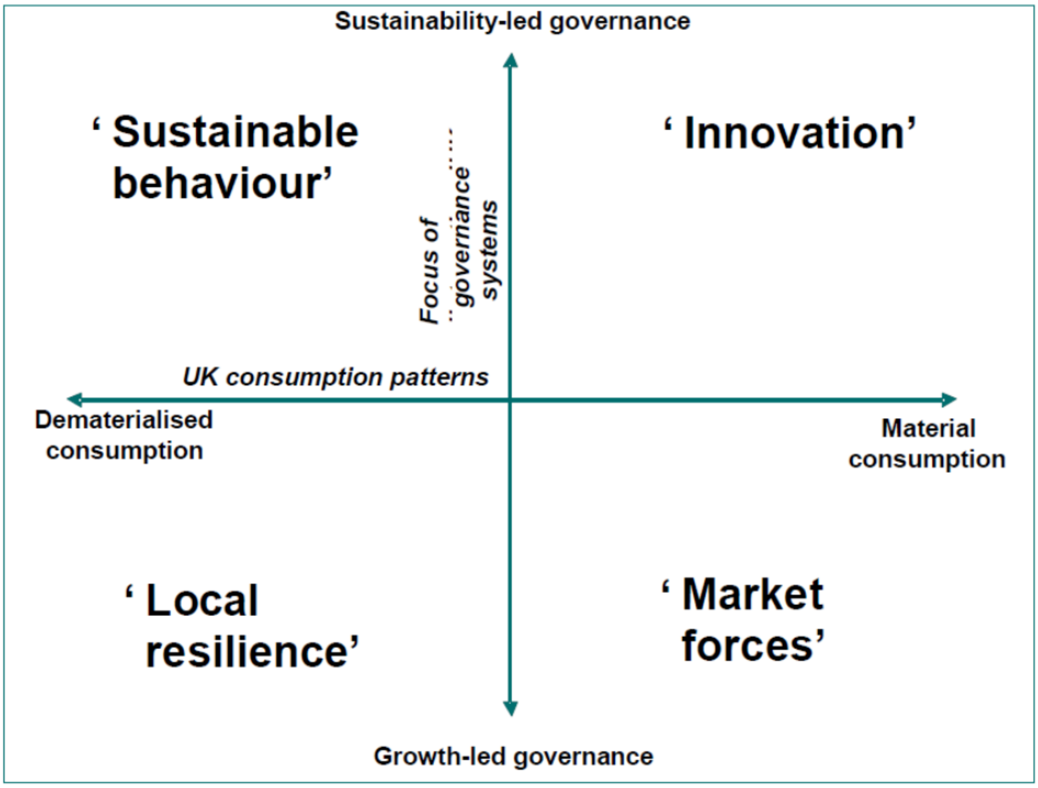


Figure 2.3.0.1: Axes of uncertainty, example from EA (2010).

grounded, defendable, and wholly appropriate including key world drivers (social, technological, economic, environmental, political, organisational, and security)" that continue to be relevant today (Hunt et al., 2012a, p. 23 (762)).

The GSG defined, refined and checked repeatedly for internal consistency two scenario variants for each of these world end-states, producing six scenario archetypes (Raskin et al., 1998). These scenarios are: Eco-Communalism and New Sustainability Paradigm (NSP) as Great Transitions; Policy Reform (PR) and Market Forces (MF) as Conventional Worlds; and Fortress World (FW) and Breakdown as Barbarisations. GSG took special care to make the scenarios a logical and plausible evolution from the world today (Gallopín et al., 1997). These are explorative scenarios which show a deep understanding of the key fundamental drivers of change, are thought provoking and have gained credibility precisely because people can imagine living there (Hunt et al., 2012a, 2012b).

In addition, GSG quantified four of these scenarios (NSP, PR, MF and FW) using their PoleStar System (Electris et al., 2009; Hunt et al., 2012a; Kemp-Benedict et al., 2002; Tellus Institute, n.d.-b). These scenarios are integrated —considering major economic, social, cultural, institutional, technological and environmental questions at the same time—, disaggregated by regions and sectors, and they convey this information in various points in the future until the year 2100 (Raskin et al., 2010). And, very importantly, they extend enough to the extremes of plausibility and are sufficiently distinct to cover a wide range of possible futures to be relevant to anyone considering scenario-based studies (Hunt et al., 2012a, 2012b). Table 2.3.0.1 shows the four archetypal social visions for the future that these scenarios represent.

Table 2.3.0.1: Archetypal social visions for the future that the four quantified GSG scenarios represent (adapted from (Hunt et al., 2012a)).

NSP	PR	MF	FW
A world where new human values and new approaches to development emerge.	A world that is influenced by a strong policy push for sustainability.	A world that evolves gradually, shaped by dominant driving forces.	A world that succumbs to fragmentation, environmental collapse, and institutional failure.

These four scenarios were adapted to urban UK in 2050 by BRE's Designing Resilient Cities (DRC) (Lombardi et al., 2012). DRC is designed to study the performance of sustainable interventions in the urban environment. This aim partly covers the study of the residential energy demand in the UK and, thus, its scenarios partly characterise this domain. This makes the scenarios from DRC a convenient choice for the tool developed in this work. However, to perform an in-depth analysis of the residential energy demand, these scenarios have to be adapted. This adaptation and further information about DRC can be found in Chapter 4. There, a set of indicators are characterised to reflect the most important of the determinants of the energy consumed in buildings —listed in the previous section— which were not already characterised in the scenarios.

2.4 Projecting disaggregated data into scenarios

During the construction of futures scenarios, aggregated data is commonly projected to characterise them. The tools developed to that effect are usually complicated computer models (*e.g.* Integrated Assessment Models (IAM), System Dynamics (SD) models, etc.) which are able to simulate the expected behaviour of some aggregated data in different future scenarios (Chen et al., 2016; MEDEAS, n.d.; Rye & Jackson, 2018).

Supplementing scenarios with the characteristics of new indicators or adapting them to new domains or environments is not uncommon (Banchs-Piqué et al., 2020; Gerst et al., 2014; Lombardi et al., 2012). These tools developed to produce scenarios can sometimes also project data into the scenarios they generated to quantify indicators which were not originally characterised (Tellus Institute, n.d.-b). For example, (Gerst et al., 2014) have used the PoleStar System (Tellus Institute, n.d.-b) to project into the scenarios developed by the GSG data concerning the Stockholm Resilience Centre's (SRC) boundaries defining a safe operating space for humanity —these are environmental boundaries that, if transgressed, entail a risk of "crossing thresholds that will trigger non-linear, abrupt environmental change within continental- to planetary-scale systems" (Rockström et al., 2009, p. 1)—. The resulting projections show the expected values of the data in each scenario, determining which boundaries have been crossed.

The PoleStar System was originally used by the GSG to quantify four of their scenarios representing the archetypal social visions for the future they developed (NSP, PR, MF and FW). In opposition to conventional modelling data projections used to quantify scenarios, which are rigid and can explore only a narrow aperture around business-as-usual futures, PoleStar is flexible and designed to be able to also quantify uncertain scenarios with discontinuous developments (Tellus Institute, n.d.-b). This tool has also been used by international institutions (*e.g.* United Nations, OECD) and other groups to create and quantify a number of scenarios (Hunt et al., 2012b). However, this tool does not project disaggregated data. Indeed, the projection of disaggregated data into existing or new scenarios with a simple method does not exist.

A projection of a data set into a scenario is the transformation of the aggregated information held in the data set, so that it approximates the likely behaviour those data would have on the characteristics of that scenario. If the data projected is disaggregated, the information of the different behaviours of distinct groups of agents can be taken into account and analysed, giving direct detail and depth to the analysis of the outcomes.

Although there is a historical difficulty to obtain disaggregated data, increasingly significant volumes of data are being generated on a daily basis at a pace which constantly accelerates (DOMO, 2018; Peters, 2012). Particularly, the growth of advanced metering infrastructures associated to smart energy systems and smart grids (smart metering devices and other end-user side measuring terminals)(Zhou et al., 2016; Zhou & Yang, 2016), promise a boost in the availability of household energy demand data.

If such data can be cost effectively considered in future scenarios they could help us make better decisions in the present and ensure we are better equipped to manage future uncertainty. These concerns are particularly apposite for the fields of sustainability and sustainable development, which have an intrinsic focus on the future (Holden et al., 2014; Rizzi, 2015; van der Hel, 2018), and for any domain which involves long asset lives, like buildings.

2.5 Putting it together

The UK has recently committed to net zero carbon emissions by 2050 (HM UK Parliament, 2019), and it recognises that the built environment plays a crucial role in achieving this target (DECC, 2009). In addition, the government has forecasted an increase in electricity demand of 60% by the year 2050 and a peak demand that mirrors this increase (National Grid ESO, 2019; SAVE, n.d.). Domestic consumers represented the largest share of the electricity demanded in UK in 2018, with 30% of total electricity demand. This same year, domestic consumers represented the largest share of gas demand as well, larger than that used for electricity generation (BEIS, 2019). Besides, household size has been declining since 1961 and is projected to continue to decline until 2039 (UK Government, 2016), and the dwelling stock of Great Britain has been steadily increasing in the period

1951-2019 (Closer, n.d.; UK Government, 2020). However, energy consuming processes like use of appliances do not necessarily scale with household size —*e.g.* almost 100% of household use laundry and refrigeration appliances (Hulme et al., 2013)—, boosting the risk of increasing domestic energy demand.

This is not an isolated problem of the UK, Spain (Forte, 2020) and Germany (Statistical Data Warehouse, n.d.) are other examples of countries with an steady increase of dwellings. And, although the household energy demand in the EU in the period 2005-2016 shows a slight tendency to decrease, more reductions are needed for Europe to achieve its low-carbon growth envisaged in the 7th Environment Action Program (European Environment Agency, 2018). In addition, under business as usual, the energy demand in the global building sector is expected to increase by 50% by 2050 (IEA, 2013). This projection starkly contrasts with the estimation that, to achieve the global goal of limiting the temperature rise to 2°C, the building sector has to reduce its carbon dioxide emissions by 77% compared with the 2013 baseline (IEA, 2013).

Therefore, carefully planning the future of the residential sector and the way it uses energy —as well as its energy-supply technologies and networks— is key to meet the commitment the UK took of net zero carbon emissions by 2050 and the global goal to limit the temperature rise to 2°C.

Traditional decision support methods used to manage future energy demands mostly produce forecasts based on past trends. However, history does not usually follow a straight path. This often results in that projected energy demands deviate from actual demands. In addition, buildings and their energy systems have long asset lives. In consequence, any solution, regulation and plan based on such projections may stop delivering their advantages during their lifespans even if they avoid past mistakes. This would not only lead to these assets growing stranded, resulting in large amounts of effort and resources being lost, but also to failing to meet the local and/or global emissions goals, putting more pressure to an already tensioned natural system.

For this reason it is key to take future uncertainty into account when designing such interventions, so that they continue to function as designed regardless —or almost regardless— how the future evolves. Specifically, providing a tool to improve the design of these interventions in the UK can also help other countries and regions tackle this problem, especially if the tool can be accommodated to any region.

Sets of explorative futures scenarios which span to the extremes of plausibility are good aids for performing futures analysis and helping design such resilient interventions. In particular, the scenarios of DRC are especially apt to study the future of the household energy demand in UK, as they are already tailored to the UK —particularly to urban UK in 2050, a time distant enough to be substantially different from the present (Caputo et al., 2012)— and their aim partly covers the study of the household energy demand —they only have to be adapted with the characteristics of some of the factors determining this demand—.

A futures analysis of the determinants of the energy demand in households using these scenarios would identify a range of distinct plausible paths that UK residential demand could take in the future. Thus reducing the uncertainty faced in the decision-making processes affecting it, and so, maximising the chances that the decisions taken deliver their benefits regardless the future.

If, in addition, this futures analysis provides quantitative insights about these plausible futures, these paths can be better defined. For this, household energy demand data could be projected into these scenarios. Particularly, if the data projected would be disaggregated, *i.e.* of a set of distinct households, these projections could directly account for the specific behaviours of distinct groups of households. However, as seen in the previous section, a simple tool (no dependency between variables, simple concept and mathematics) to project disaggregated data into future scenarios is currently not available.

For this reason, the aim of this thesis is to provide a simple scenarios-based tool that, by projecting disaggregated household energy demand data, allows the analysis of the impact that future uncertainties have on this demand. In order to achieve this aim, some conditions are needed but not sufficient in isolation. In addition, these conditions build on each other.

First of all, a set of factors determining the energy demand of households must be defined. Similarly, a set of scenarios into which to project the data must be available and must characterise these factors. For that, the scenarios from DRC must be adapted. In order for the scenarios to convey distinct and enough information in this domain, these factors must be as uncorrelated as possible and not leave unexplained gaps. These scenarios represent urban UK and, therefore, the projections obtained inform about the future evolution of the data projected in the UK. However, the tool can be adjusted to study the future evolution of the data in any region by using scenarios representing the region of interest.

These conditions constitute the basis for using the tool and they are worked on Chapter 4. The crucial step is, however, the development of the tool. Providing such a tool entails developing it as well as testing it with real data to evaluate its usefulness. For that, an analysis of the outcomes and of the subtleties of using the tool is performed. However, a deep analysis of the consequences of these outcomes or the development of a systematic way to aggregate projections are outside the scope of this thesis.

The derivation of the mathematical framework used to obtain the projections and the method to use it are presented in Chapter 5. This, together with de supplementing of the DRC scenarios and an explanation of the theoretical framework used in this thesis comprise Part II - *Development of methods* of the thesis.

Testing the tool with real data and aggregating the projections is done in Chapters 6 and 7 respectively, which comprise Part III - *Projecting household energy data into future scenarios* of this thesis. Finally, the evaluation of the usefulness of the tool is discussed in

Chapter 8 which, together with the conclusions in Chapter 9 comprise Part IV - *Discussion and conclusions* of the thesis.

Part II

Development of methods

Chapter 3

Theoretical framework

Real knowledge is to know the extent of one's ignorance.

— Confucius

This chapter first provides some context about the particularities of the theoretical framework of future studies and scenarios in particular. Then, it gives an explanation of the specific theoretical frameworks with which the supplementing of the scenarios and the development of the mathematical framework where approached, as well as of the overall research design.

3.1 Foresight's theoretical framework

Future studies in general raise remarkable challenges for philosophers. They are a subclass of thought experiments and, therefore, belong to the realm of imaginative projections; they are speculations about the long-term (Aligica, 2005). In addition, in the history of future studies there has been a paradigm shift where the field transitioned from forecasting to foresight (Shala, 2018).

Forecasting "consists of tools and methods that use knowledge (...) in order to plan and predict the future". Foresight, on the other hand, "enables the creation of alternative futures for today's decision making" (Shala, 2018, p. 49).

This is a deep change in the way futures thinking is approached; an array of (more or less) plausible futures displaced a single prediction of what the future could bring. This multiple futures approach introduces even more epistemic uncertainties regarding foresight. Not only does foresight deal with things that do not exist and may not come to exist; it deals with things that will not exist. This is a highly dubious predicament from the epistemological standpoint. The consequence of this is that there are doubts whether foresight should be considered a science, at least in the sense of the classical epistemology, or rather an art. However, this *range of speculations* —foresight— are indispensable in practice and, therefore, need an epistemological justification (Aligica, 2005; Shala, 2018).

Foresight cannot be classified by any of the canonical approaches to scientific knowledge, which is based on logic justification. It does also not fit well with the scientific positions in the different scientific fields. The epistemic deficiencies of foresight are above all evident when they are compared to the epistemic standards in experimental sciences. The scientific method is based on its ability to take measurements to explain reality. It is clear that propositions about the future cannot be rationally justified based on inductive or deductive approaches stemming (directly or indirectly) from measurements and relevant well established theories (Shala, 2018).

However, although foresight cannot be ascribed to any existing scientific position, it could still be scientific. After all, thought experiments have been frequently used in science with great impact. From this point of view, for foresight to be scientific, it would need to formulate a theoretical framework to enable its validation and to address other aspects like its objectivity and truth (Shala, 2018).

Furthermore, seen from another point of view, the advancement of its methods and its adaptation of procedures and theory to framework conditions, make foresight seem to be a scientific field. See, for example, the classification of foresight methods done by Popper (2008, p. 66) in Figure 3.1.0.1 —it shows the methods used in foresight, classifies them by their type (qualitative, quantitative and semi-quantitative), and arranges them in two axis in an epistemic framework depending on their stand between being creativity- vs. evidence-based, and expertise- vs. interaction-based—. However, there is much disagreement about whether foresight can be considered a scientific field or not (Aligica, 2005; Shala, 2018).

In summary, on the one hand foresight makes it possible to design procedures which are scientifically valid and maintain objectivity. But on the other hand it is ontologically impossible to make a true claim about the future, to create knowledge. Therefore, foresight could be defined as a special kind of applied science (Shala, 2018).

To argue for or against foresight being an applied kind of science is, obviously, not within the scope of this thesis. Yet, this introduction shows why some deny foresight to be epistemically valid. In any case, this issue does not have much relevance in the field, as foresight is driven by practice rather than by theory. Alternative futures have to be based on contemporary scientific knowledge and be useful to tackle problems which would be, otherwise, overlooked; they are not to be proven right or wrong by future research. The aim of foresight is to serve the needs for "future-proved" planning rather than to contribute to scientific progress.

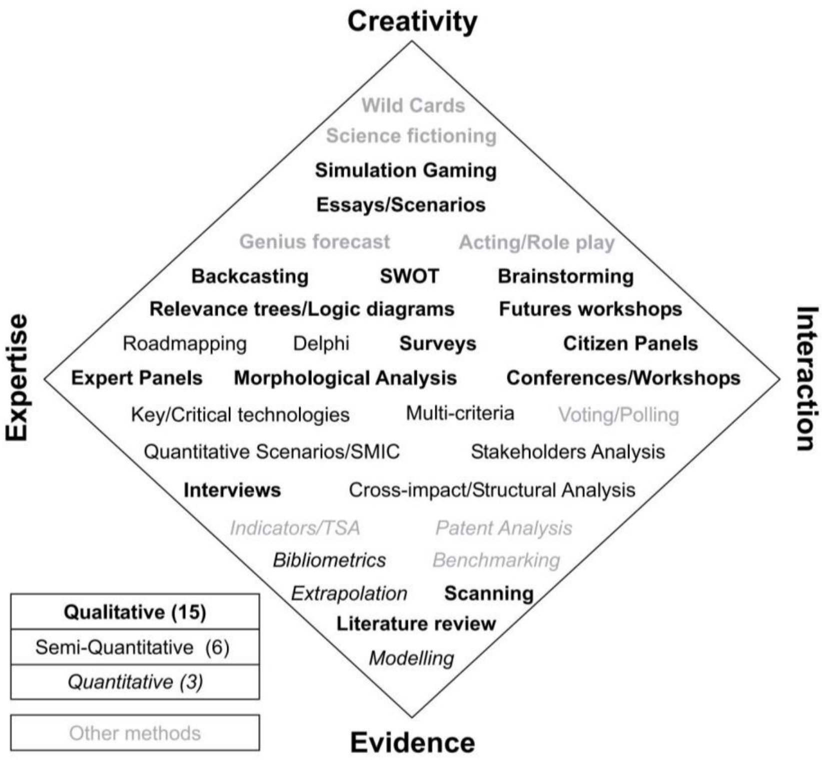


Figure 3.1.0.1: Foresight diamond: depiction of the methods used in foresight (from Popper (2008)).

3.1.1 The case of scenarios

Scenarios, being one of the methods used in foresight as they are (see Figure 3.1.0.1), raise remarkable philosophical challenges. They are of great importance in the real world, but they belong to the realm of imaginative projections.

In the philosophical sense, a scenario is an effort to draw consequences of hypothesis through a process of reasoning (Aligica, 2005). Although this may be grounded in well established facts, it refers to future developments, *i.e.* possible developments, some of which will never exist.

As explained in Chapter 2, scenarios help users to process complex information. They express complex and divergent characteristics which would otherwise be almost impossible to process, with the simplicity of concrete and coherent narratives.

As Aligica (2005, p. 6 (820)) points out, "[i]n order to find out what kind of new knowledge is produced in scenarios, one needs to look at the very foundations of the process. Seen as experiments, scenarios are thought experiments, and as such they do not directly deal with the empirical reality. (...) A new configuration of knowledge emerges out of the exercise [of deducing a conclusion from premises] in spite of the fact that no original empirical findings are involved."

Thought experiments are different from ordinary experiments in that they manipulate parameters of mental pictures of the world, rather than actual aspects of the world. Therefore, the findings are not empiric, they are conditional. However, this process reconfigures information in a way that provides new knowledge about the situation and an increased understanding of the model. This means that, rather than providing insights or direct answers to a problem, scenarios help to evaluate it in a rational way. This is the understanding and knowledge that scenarios provide (Kahn & Wiener, 1967; as cited in Aligica, 2005; Schwartz, 2012)

In order for scenarios to produce true understanding and knowledge, a battery of hypotheses, intuitions and theories have to be, explicitly or implicitly, used in their building. However, as important as they are, theory, models and frameworks should not hide the importance of data in the epistemic performance of scenarios. The data on which a scenario is based are crucial in their performance, and need to be as close as possible to the real situations and domains they portray. Scenarios open in a range of future branches; and so, the more grounded they are in the reality before that opening, the better they are (Aligica, 2005).

3.2 Adopted theoretical framework

The structure followed to explain the theoretical framework used in each part of the research is "The Map", Figure 3.2.0.1, by Hertz and Mancilla (2019). This map represents key elements of the research process. However, the scope of "ologies" is not limited to those appearing in this figure.

3.2.1 Supplementing scenarios

The research philosophy used to develop and characterise the indicators to supplement the DRC scenarios was pragmatism. The criterion used in a pragmatic theory of truth relates to how well the outcomes serve their purpose. The truth criterion could also be considered to be truth as coherence, because the supplemented indicators had to be coherent with the existing scenarios. However, as seen above (Section 3.1.1), scenarios fall in the realm of possibilities, not realities. Therefore, this would be a dubious consideration. Pragmatism is not only a truth criterion, it is also an epistemology and some authors argue that it can be considered an ontology as well (Frankel Pratt, 2016; Mitchell, 2018). Pragmatism is a position used when the choice between paradigms is not practical.

The methodology used to supplement the scenarios was mostly deduction. However, it is a particular case of deduction similar to that explained in Section 3.1.1. Instead of using established premises (laws, measurements...) to obtain a conclusion, the conclusion is reached from premises arising from the scenarios, *i.e.* not real-world premises, using established laws to support them. In some specific cases where the information to derive

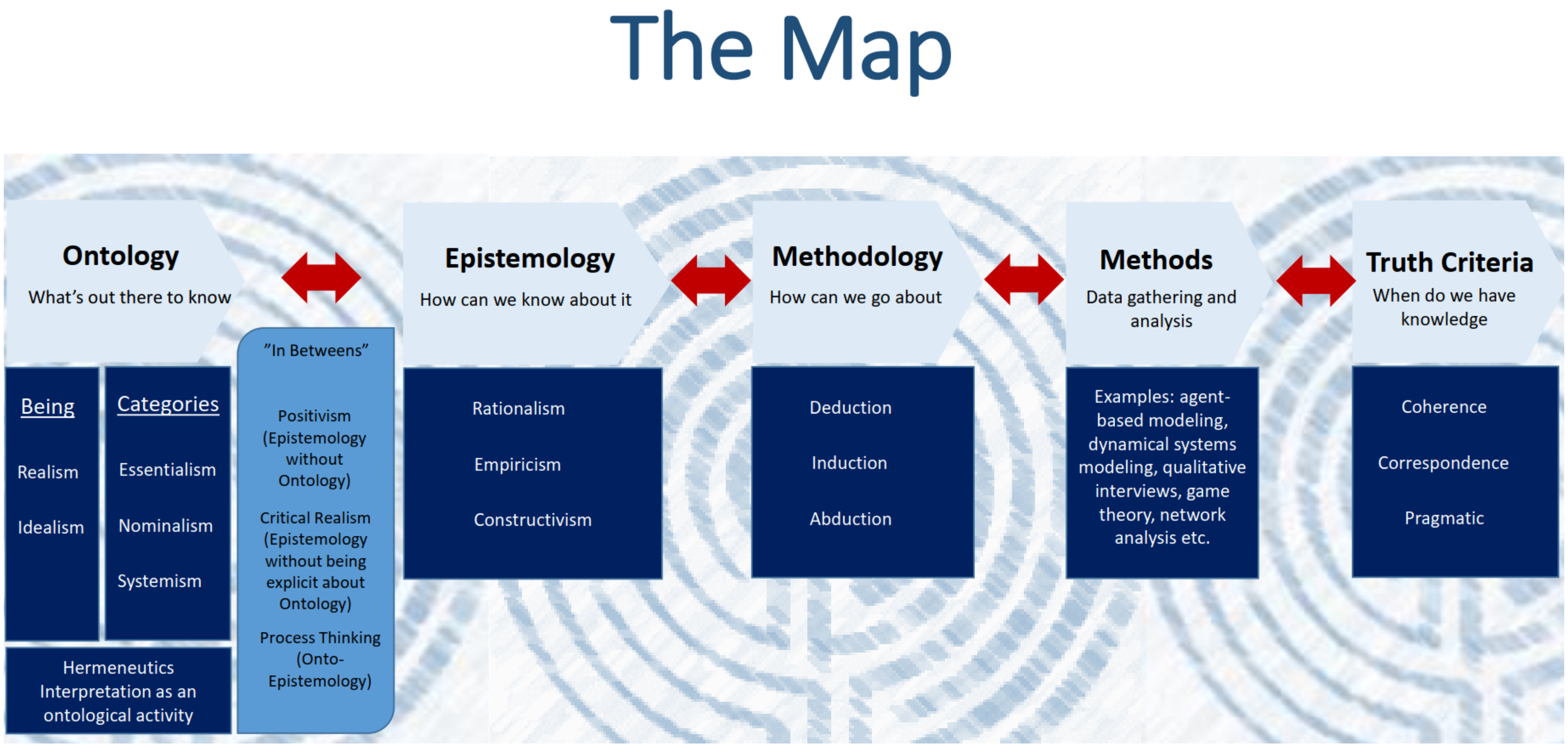


Figure 3.2.0.1: The Map: this map represents key elements of the research process (by Hertz and Mancilla (2019)).

a new indicator was scarce or vague, induction was used. However, abduction is not considered to be the methodology used because the instances when induction was used were very limited (only once, for the indicator 'Attitudes to energy efficiency and sustainability') and it was exclusively used as last resort, while abduction implies a premeditated back and forth use between deduction and induction.

The method used in this case was a review of the scenarios literature, as well as of the literature on the determinants of household energy demand. In addition, for each supplemented indicator, a brief review of the literature related to it was done to derive its characteristics. As Figure 3.1.0.1 shows, literature reviews are qualitative methods based on evidence.

3.2.2 Mathematical framework

The approach to conceive and develop the mathematical framework to project data into scenarios was close to being positivist. Positivism searches for causal relationships and regularities, which is what was here done (Mitchell, 2018). This means that science informs the investigation. However, it is sustained on the narrative and characteristics of scenarios, therefore, this is most likely "beyond" science. Therefore, it could be considered to be critical realism instead.

The research approach to develop the mathematical framework was deductive, and the method is a very simple case of modelling, which is an evidence-based quantitative method. As in the previous case (Section 3.2.1), the truth criterion here is between pragmatic and coherent.

In order to use the mathematical framework to project disaggregated data, pragmatism was clearly the approach used. To produce each projection, the ratios of the different groups of households in the future scenarios had to be derived from the scenarios' characteristics. These derivations are not exact and the precise value of the ratios could vary. However, this does not hinder the utility of the projections as long as these ratios truly follow the characteristics of the scenarios.

3.3 Research design

The overall design of this research consisted of four phases; these can be seen in Figure 3.3.0.1. In phase one, a broad understanding of future scenarios and the determinants of household energy demand was gained by means of a review of the relevant literature. In phase two, the indicators needed for DRC to give a detailed picture of the energy demand in households were developed. To do that the knowledge gained in phase one, plus brief reviews of the literature related to each indicator were used. With this exercise a much deeper understanding of scenarios was gained. Phase three consisted of devising a method to project disaggregated data into future scenarios and developing its mathematical formalism. To conceive this method the knowledge gained in phases one and two while working and supplementing the scenarios were crucial. And, finally, phase four was the validation of the mathematical framework and the new indicators. Here, real household energy demand data were projected into the supplemented scenarios using the mathematical framework previously developed. Then, these projections were aggregated by two different methods to obtain a picture of the household energy demand in each scenario and to test the robustness of these results. Finally, the results were analysed.

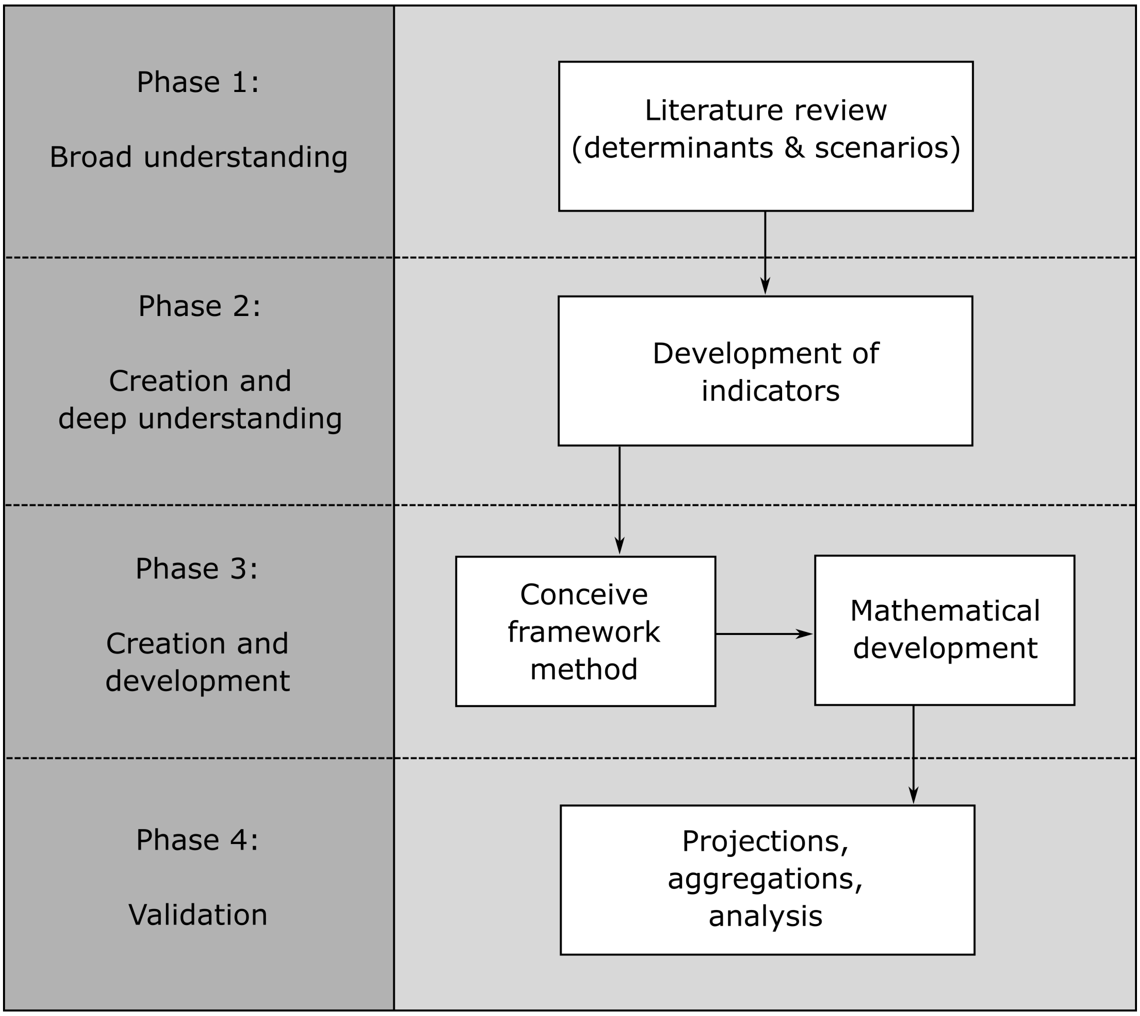


Figure 3.3.0.1: Research framework of this study.

The methods used to supplement the scenarios and derive the mathematical framework show the ambivalence of foresight studies, which fall between being a science and an art. These methods were literature reviews and modelling, which are the most evidence-based (scientific) methods from the foresight diamond. However, they are used to complement scenarios, which are almost the most creativity-based (art) methods in the foresight methods diamond, Figure 3.1.0.1.

3.4 Ethical considerations

The University of Portsmouth research ethics committee approved the research undertaken for this thesis. As it does not involve living participants there are no other requirements than that the data used must be anonymised, which they are. The ethics form of this study can be found in Appendix E.

Chapter 4

Supplementing DRC scenarios

There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns —the ones we don't know we don't know—.

— Donald Rumsfeld

This chapter presents a method to supplement futures scenarios with a typical architecture and a series of indicators supplementing Designing Resilient Cities (DRC). These indicators convey detailed information about households and the way they use energy which was missing in DRC.

The chapter starts with a brief explanation of DRC and the architecture of its scenarios, and a discussion of the main determinants of the household energy demand. These are followed by an explanation of the method used to define and characterise these indicators. Subsequently, it introduces the resulting indicators and their context information, and a short case study demonstrates the use of the new indicators. Finally the method is discussed, and a summary of the chapter and its conclusions are given.

4.1 Designing Resilient Cities

In the futures scenarios literature, there exist different types of scenarios, tools and methods designed to help perform futures analysis in a wide range of contexts. One tool that can easily be adapted to study household energy demand in the UK is BRE's Designing Resilient Cities (DRC) (Lombardi et al., 2012). DRC, with its *Urban Futures Method* (Rogers et al., 2012), is designed to study the performance of sustainable interventions in the UK urban environment. This tool was developed by a project called *Urban Futures*, which published it in 2012 in parallel to a themed issue of *Engineering Sustainability.* That themed issue was dedicated to the use of futures scenarios for evaluating the resilience of sustainable solutions in the urban environment in the UK (Rogers, 2012).

Urban Futures used as the basis for its scenarios those developed by the GSG, a project from the Tellus Institute. These scenarios are integrated —considering major economic, social, cultural, institutional, technological and environmental questions at the same time—, disaggregated by regions and sectors, and they convey this information in various points in the future until the year 2100 (Raskin et al., 2010). These are explorative scenarios that cover a broad range of possible directions in which the future could unfold, and they can be used to formulate 'what-if?' questions (Rogers et al., 2012). GSG took special care to make the scenarios a logical and plausible evolution from the world today and internally consistent (Gallopín et al., 1997). *Urban Futures* adapted four of these scenarios —New Sustainability Paradigm (NSP), Policy Reform (PR), Market Forces (MF) and Fortress World (FW)— to the UK urban environment in 2050, and developed DRC to help evaluate the resilience of sustainable urban interventions in this domain (Boyko et al., 2012; Lombardi et al., 2012).

These scenarios extend to the extremes of plausibility and are sufficiently distinct to cover a wide range of possible futures (Hunt et al., 2012a). In addition, the year 2050 is far enough in time that the descriptions could be different from the present, yet not too advanced that decisions taken based on them could not be reasonably evaluated with current indicators. This year was chosen as the year the project "dropped into". This allowed *Urban Futures* to characterise the scenarios without having to identify plausible pathways for getting there (Boyko et al., 2012).

Table 4.1.0.1 shows the key drivers and a brief description of the scenarios characterised in DRC, which are also well described by their names. In addition, a list of the indicators they characterise is available in Appendix A, and the tables with their characteristics are provided within the electronic data that comes with the thesis (see Appendix D). If further description of the scenarios is sought, brief general narratives can be found in the following literature: for the general GSG scenarios, see the monograph by Hunt et al. (2012b); for a version representative of OECD countries, see the paper by Rogers et al. (2012); and for further description of the UK urban version developed by *Urban Futures*, see the paper by Boyko et al. (2012).

The *Urban Futures Method* "aims to broaden the way we think about the form, function, and context of urban development and regeneration by focussing on the likely long-term performance of today's urban design solutions, and their associated vulnerabilities" (Lombardi et al., 2012, p. ix). This aim partly covers the study of the energy demand of the UK's residential sector. This makes the scenarios from DRC a fitting choice for the tool developed in this thesis. However, to do an in-depth analysis of this domain, these scenarios have to be adapted. Fortunately, they are designed in a way that new indica-

Table 4.1.0.1: Brief description and key drivers (in italics) of the scenarios from DRC (adapted from Lombardi et al. (2012)).

New Sustainability Paradigm (NSP)	Policy Reform (PR)	Market Forces (MF)	Fortress World (FW)
Equity and sustainability arising from society.	*Economic growth with greater equity.*	*Competitive, open global market.*	*Protection and control of resources.*
An ethos of 'one planet living' facilitates a shared vision for more sustainable living and much improved quality of life. New socio-economic arrangements result in changes to the character of urban industrial civilisation. Local is valued but global links also play a role. A sustainable and more equitable future is emerging from new values, a revised model of development and the active engagement of civil society.	Policy Reform depends on comprehensive and coordinated government action for poverty reduction and environmental sustainability, negating trends toward high inequity. The values of consumerism and individualism persist, creating a tension with policies that prioritise sustainability.	Market Forces relies on the self-correcting logic of competitive markets. Current demographic, economic, environmental, and technological trends unfold without major surprise. Competitive, open and integrated markets drive world development. Social and environmental concerns are secondary.	Powerful individuals, groups and organisations develop an authoritarian response to the threads of resource scarcity and social breakdown by forming alliances to protect their own interests. Security and defensibility of resources are paramount for these privileged rich elites. An impoverished majority exists outside the fortress. Policy and regulations exist but enforcement may be limited. Armed forces act to impose order, protect the environment and prevent societal collapse. (ratio 35:65)

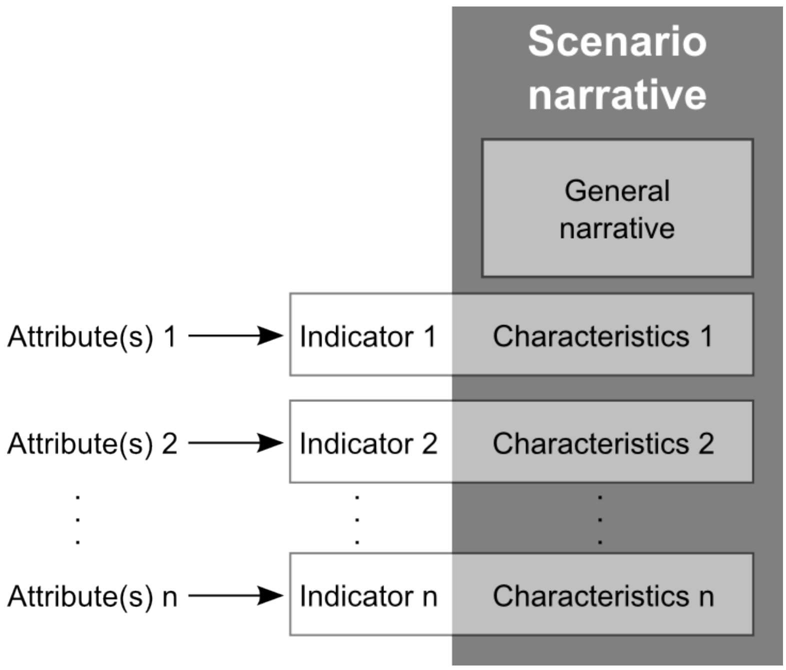
tors and characteristics can be added to them; additionally, new scenarios could also be incorporated into the set if needed (Boyko et al., 2012).

Thus, the objective of this chapter is to adapt the scenarios from DRC to the study of the residential energy demand in UK. This is done by adding a set of indicators related to household energy demand or its causes and developing their characteristics for each scenario, which increases the detail of information that the scenarios provide in this domain. A short case study is also presented afterwards to demonstrate the usefulness of these additions.

4.1.1 DRC scenarios

The scenarios from DRC are explorative scenarios. These scenarios map a plausibility space so it can be explored or studied (Boyko et al., 2012; Foresight Horizon Scanning Centre & Government Office for Science [FHSC][& GO-Science], 2009; Rogers et al., 2012; Schwartz, 2012). They help thinking about the future in a structured way and based on a set of assumptions that have been previously defined.

The narrative of the scenarios in DRC comprises a short general narrative and the characteristics of a set of indicators. This type of architecture is common in the scenarios developed within the futures studies. The general narrative describes briefly and precisely the main aspects of the scenario, and the characteristics of the indicators, its details. The indicators represent the attributes of the system —for example, the size of the population in the scenario— and they can represent any aspect(s) of interest. They are accurately defined, with a unit of measurement and normally their value in the reference/base scenario or some kind of benchmark. The characteristics of an indicator quantify or qualify, with short statements, its performance under each scenario, normally in relation to the base (Boyko et al., 2012). In the case of DRC, for ease of use, the trend in relation to the reference is also shown with an arrow. See Figure 4.1.1.1 for a graphical depiction of the narrative composition of scenarios with this architecture, and find the tables with the characteristics of the DRC indicators within the electronic data (see Appendix D).



The narrative of each scenario comprises a brief general narrative describing the main aspects of the scenario and the characteristics describing the performance of a set of indicators in the scenario. These indicators represent one or more attributes of the system.

Figure 4.1.1.1: Typical scenario architecture (also used by DRC).

Note that all scenarios are defined by the same set of indicators; the differences in the characteristics of these indicators between the scenarios are what, in conjunction with the general narratives, portray the differences between the scenarios. In order for the scenarios to provide coherent information, it is important that the characteristics of the indicators are internally consistent and that they are based on the relevant literature. Otherwise, the characteristics of one indicator could be contradictory with those of another indicator or with the general narrative of the scenario; or the characteristics of an indicator in one scenario could give different information from those in another scenario (*e.g* scenario X may say that everyone is happy at work while scenario Y says that people work for 7 days a week, which prevents direct comparison and leaves many questions unanswered (Hunt et al., 2012b)). This is why both, GSG and *Urban Futures*, have put great effort in keeping internal consistency (Gallopín et al., 1997; Raskin et al., 2002; Raskin et al., 1998; Rogers et al., 2012).

The use of these kind of scenarios provides information on the possible evolution of any subject of study in a range of futures. This can be valuable for many purposes. In particular, it can provide information on the performance of any proposed intervention in the different futures, thus helping improve its resilience —*i.e.* its effectiveness in all the scenarios— or, at least, informing of its weaknesses (Boyko et al., 2012; Lombardi et al., 2012; Rogers et al., 2012). This is precisely what DRC does.

4.2 Main determinants of household energy demand

As explained in Chapter 2, the factors determining household energy demand are intricate and complex. In different studies —and often also within studies—, different factors are mentioned which are either very correlated, partially overlapping or mean roughly the same. Therefore, it is not straightforward to curate a list with the most significant of these determinants, and which minimises overlapping and gaps between determinants.

The determinants of the energy consumed in buildings are usually classified in: (1) building factors, (2) socio-economic factors, and (3) occupants' behaviour (which is difficult to measure) (Gram-Hanssen, 2014; Huebner et al., 2016).

The main determinants of household energy demand that appear in the literature are related to the type of the building, its energy efficiency, the size of the dwelling, the age of the building, the size and age distribution of the household, their level of education and income, their energy-related behaviours, their use of appliances and heating, the time they spend at home, energy price and energy efficient equipment, and the climate the building is exposed to (Bhattacharjee & Reichard, 2011; Huebner, Hamilton, Chalabi, et al., 2015; Huebner et al., 2016; Jones et al., 2015; Jones & Lomas, 2015; Kavousian et al., 2015).

Some of these determinants are totally or partly characterised in the DRC scenarios already. In addition, some fall outside the scope of the future scenarios from DRC (*e.g.* those related to the climate) and some are only proxies for other determinants (*e.g.* age of building is a proxy for its energy efficiency and other factors such as type of building). For the others, a set of new indicators has been characterised in an iterative process described in the next section. However, these are not the only determinants that needed to be taken into account. As it is not the same to consume electricity or gas —these are the main sources of energy used in UK households—, it is important to determine the energy source used for space and water heating (largest slice of the energy used in UK households (Palmer & Cooper, 2013)). Similarly, the energy demanded by a household to the utilities is not necessary the same as the energy they consume. Therefore, self-generation and storage of energy were also taken into account when defining the new indicators.

4.3 Developing domestic energy demand indicators

This section describes the method used to define the indicators that needed to be developed to study the energy demand of the domestic sector in the context of the DRC tool (Lombardi et al., 2012), as well as how their characteristics for the four futures scenarios were developed. For a generalised and systematic form of this method see Section 8.4.1.

The system attributes that the indicators developed here represent are the main factors determining the household energy demand described in the previous section and in the references it contains. These sources were used to rank factors in order of importance.

Factors that overlapped significantly with each other and with those from DRC were synthesised into a single indicator (*e.g.* the factors 'number of rooms', 'number of bedrooms' and 'number of floors' were blended into 'total floor area'); sets of factors conveying redundant or overlapping information were grouped to form a smaller number of indicators when this did not imply significant loss of information (*e.g.* three factors grouped to create two indicators); and factors with smaller or no clear impact in the energy demand of households, or without reliable information to characterise an indicator, were discarded (*e.g.* the infancy of domestic energy-storage technologies would have made the analysis of their future evolution very uncertain).

The remaining factors outlined the indicators that needed to be characterised. For that, first they had to be accurately defined or justified. In addition, the question that the indicator answers was formulated.

Before developing the characteristics of an indicator, the current value of the indicator was found, and the factors on which the indicator depends were listed. Then, the characteristics of the indicators that give information about these factors (both from DRC and from the list of indicators developed for this analysis) were put together. If needed, missing information about any of the factors was added from the literature related to GSG (Tellus Institute), as well as the characteristics of other related indicators and/or context information extracted from the general narrative of the scenarios. See the indicators and other information used to derive the characteristics of each new indicator in Table 4.3.0.1.

Table 4.3.0.1: Indicators and other information used to derive each of the new indicator's characteristics (continued on next page).

Indicator	Indicators from DRC	Indicators developed in this work	Other factors and sources
Adoption of domestic (or community) microgeneration	• Public service spending • Energy efficiency of the building and urban morphology	• Energy prices (domestic) • Attitudes to energy efficiency and sustainability	• Information in the E[R] report • General narratives from DRC

Table 4.3.0.1 – *Continued from previous page*

Indicator	Indicators from DRC	Indicators developed in this work	Other factors and sources
Attitudes to energy efficiency and sustainability	• Attitudes to consumerism • Civic activism	–	• General GSG narratives
Average dwelling (usable) floor area	• Average household size • Housing affordability • Urban dwelling density • Settlement pattern (city scale) • Settlement pattern (neighbourhood scale) • Need for affordable housing	• Type of building	• General GSG narratives
Average number and frequency of use of electric appliances	• Average household size • Attitudes to consumerism • Income inequality	• Attitudes to energy efficiency and sustainability	• Information in the technical document
Dwelling area per occupant	• Average household size • Household overcrowding	• Average dwelling (usable) floor area	–
Energy poverty	• Energy efficiency of the building and urban morphology • Income • Income inequality • Public service spending • Community cohesion	• Energy prices (domestic) • Adoption of domestic (or community) microgeneration	–
Energy prices (domestic)	–	–	• Information in the E[R] report • Information in the technical document • Table generation tool

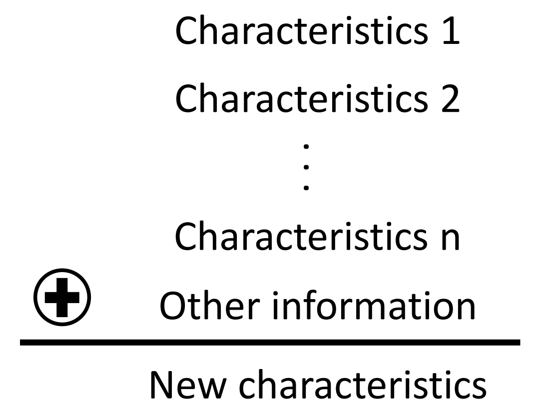
Table 4.3.0.1 – *Continued from previous page*

Indicator	Indicators from DRC	Indicators developed in this work	Other factors and sources
Type of building	• Adaptability of buildings and supporting infrastructure to new use • Settlement pattern (city scale) • Settlement pattern (neighbourhood scale) • Urban dwelling density • Total amount of green space • Urbanisation • Land use • Planning policy • Planning adherence	–	• General narratives from DRC
Use of electric space (and water) heating	–	• Adoption of domestic (or community) microgeneration • Attitudes to energy efficiency and sustainability • Energy prices (domestic)	• Information in E[R] report • Information in the technical document

References: E[R] report (Greenpeace, 2015), general narratives from DRC (Lombardi et al., 2012), general GSG narratives (Hunt et al., 2012b), technical document (Electris et al., 2009), table generator tool (Tellus Institute, n.d.-a).

With this information, the narrative for the characteristics of the new indicators is derived for each scenario, and their general trend in relation to the baseline is symbolised by an arrow. Figure 4.3.0.1 shows an analogy between the process to derive the characteristics of a new indicator for one scenario and a sum: the added information given by the characteristics of the relevant indicators and other relevant information "logically produces" the characteristics of the new indicator as a result.

As many indicators depend on each other, iterations of the whole process helped improve the final result and maintain internal consistency. Generally, for clarity, a short review of the information put together for each scenario was written (see Table 4.5.0.1). In the case of isolated discrepancies between the characteristics of the indicators used to derive new indicators and the general narrative of the scenarios, the general narrative has been used. A brief justification on the choice of indicators can be found in Section 4.4.1.



The added information given by the characteristics of the relevant indicators and other relevant information "logically produces" the characteristics of the new indicator as a result.

Figure 4.3.0.1: Analogy between the derivation of the characteristics of a new indicator for one scenario and a sum.

4.3.1 Indicator 'Energy prices (domestic)'

The previous method was not used to develop the indicator 'Energy prices (domestic)', as there are many factors that influence these prices and most of these factors are not related to the indicators from DRC. Based on the fact that the GSG used previous versions of the Energy [R]evolution report (Greenpeace & European Renewable Energy Council [Greenpeace][& EREC], 2007, 2008) to develop the energy-related information of their scenarios, the basis to develop the characteristics of this indicator was the information about future energy prices from the latest Energy [R]evolution report (Greenpeace, 2015). See Section 4.5.7 for details.

4.4 Resulting indicators

The results of this work are presented here in table form (Table 4.4.0.1). The table shows the indicators developed and their metrics and baselines. Next to them, for each scenario, the table shows their global tendency in relation to the baseline (by means of an arrow) and their characteristics. These scenarios are the urban UK versions of NSP, PR, MF and FW. Part of the results that give context to this table can be found in the next section.

Table 4.4.0.1: Indicators table: characteristics of each of the new indicators for each scenario (continued on next pages).

Measure *Base*	UK urban New Sustainability Paradigm (NSP)	UK urban Policy Reform (PR)	UK urban Market Forces (MF)	UK urban Fortress World (FW) (rich|poor)
Adoption of domestic (or community) microgeneration				
	⇑	⇑	⇑	⇑ | ⇓
% of domestic energy consumption met with microgeneration *1.3% domestic (2016) and 0.1% community (2017)*	Most domestic energy consumption is met with microgeneration, mainly at the community level.	A large percentage of domestic energy consumption is met with on-site or community microgeneration.	On-site microgeneration increases, but the percentage of domestic energy met by it is not very large.	The overall adoption of microgeneration and the percentage of domestic energy met by it are slightly higher than the current one.
Attitudes to energy efficiency and sustainability				
	⇑	⇑	⇓	⇓ | ⇓
N/A *Some good intentions, less results*	People have the will to be sustainable, the information to be so is widely available and rules and society favour it. The result is a very sustainable society with people willing and able to be sustainable.	People's mindset does not change substantially from the current one. However, the government puts a lot of effort into sustainable measures to make sustainability the default option. Information is reliable and available, making it easier to act sustainably. The result is a society that is more sustainable than currently (but far less than in NSP), in particular the individuals who are engaged.	Sustainability is far from being a priority for the people, rules do not favour it in any special way, information is still poor and confusing and society does not make it easy to be sustainable. There is no big change in society's sustainable attitudes although they worsen, and society makes it as difficult to be sustainable as currently or more. The result is a society that is less sustainable.	Rich: governments try to keep up with sustainability measures, but their priority is security. People, locked up in their enclaves, are not —or do not want to be— aware of the rest of the world. Their attitudes to sustainability are almost non-existent. Poor: although some (particularly the youth) develop expectations of fairness and may dream of sustainability, they have many much more urgent issues to deal with.

Table 4.4.0.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
		Average dwelling (usable) floor area		
	⇔	⇓	⇓	⇑ | ⇓
Average usable floor area in square metres *Mean total usable floor area of 95 m^2 (2013)*	Although people tend to live together in larger households than currently, the average dwelling's usable floor area decreases slightly. This is mainly due to the increased use of flats rather than houses and is exacerbated by the cohousing movement.	As the household size decreases and there is an increase in typically smaller dwellings (flats), the average dwelling floor area decreases notably.	The average dwelling floor area decreases. The main effect is, however, polarisation: with a strong increase in dwellings with smaller than 50 m^2 of internal floor space and an increase in those with larger than 110 m^2.	Rich: the average dwelling floor area for the rich is much larger than the current one (110 m^2 being close to their lower end). Poor: the average dwelling floor area for the poor is much smaller than the current one. Most of those with dwellings larger than 50 m^2 share them and many cannot even afford to live in formal developments.
		Average number and frequency of use of electric appliances		
	⇓	⇑	⇑	⇑ | ⇓
N/A *Almost ubiquitous presence of washing machines, refrigeration and media appliances (2011)*	People tend to have and use appliances less than today.	Appliance use and ownership is similar to the current one, only slightly higher due to smaller households.	Dwellings have a larger number of appliances, and they are more intensively used than today.	Overall there are fewer appliances and these are less used because of the large weight of the poor population (35:65).

Table 4.4.0.1 – *Continued from previous page*

Measure / *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
Dwelling area per occupant				
	⇓	⇓	⇑	⇑ | ⇓
m^2/person *One occupant every 41.3 m^2 (2011-2013)*	The dwelling area per occupant decreases considerably out of choice (very homogeneously; there is almost no overcrowding).	The area per occupant decreases moderately and homogeneously, not by personal choice but due to regulations (*e.g.* favouring flats over houses, which tend to be smaller).	The average area per occupant increases to some extent. However, the main contributors are middle to higher classes; as for a part of the lower classes, it may decrease.	Rich: increase greatly their area per occupant. Poor: decrease greatly their area per occupant.
Energy poverty				
	⇓	⇓	⇔	⇓ | ⇑
% of population in energy poverty *Around 11.0% (approximately 2.5 million households) (2015)*	Better housing, the almost non-existence of poor people and the government's and society's engagement reduce energy poverty to almost zero.	The decrease in poor people, better housing and the engagement of governments contribute to a strong decrease in energy poverty.	Although inequality increases substantially, the high increase in gross domestic product is able to keep the level of energy poverty similar to the current one.	No energy poverty among the rich. Almost all among the poor are energy-poor.

Table 4.4.0.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
		Energy prices (domestic)		
p (penny sterling)/kWh *Electricity (e): 15.47 p/kWh; gas (g): 4.31 p/kWh (2016)*	e⇑ g⇓ The electricity price will increase similarly to that in MF (17.36 p/kWh). The gas price will decrease further than that in PR (3.54− p/kWh).	e⇔ g⇓ The electricity price will be very similar to the current one, 15.25+ p/kWh. The gas price will steadily decrease until 3.54 p/kWh.	e⇑ g⇑ The electricity price will increase almost steadily until 17.36++ p/kWh. The gas price will steadily increase until 6.21 p/kWh.	e⇑ g⇑ The electricity price will increase even further than that in MF (17.36+++ p/kWh). The gas price will increase but less than that in MF (6.21− p/kWh).
		Type of building		
% of the building stock *End terrace 10.4%, mid terrace 18.8%, semi-detached 27.6%, detached 22.6%, flat 20.6% (2013)*	Flats: increase. Terraced: similar with the tendency to decrease. (Semi-)detached: decrease.	Flats: increase. Terraced: slight increase. (Semi-)detached: decrease (in particular semi-detached, as people who can afford it prefer to pay more (detached) for increased privacy).	Flats: increase. Terraced: moderate decrease. (Semi-)detached: increase.	Rich: Flats: strong decrease. Terraced: slight increase. (Semi-)detached: strong increase. Poor: Flats: stay the same percentage. Terraced: decrease. (Semi-)detached: strong decrease. Appearance of large informal developments with shacks and tent-like dwellings.

Table 4.4.0.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
		Use of electric space (and water) heating		
% of households using electric space heating *8.5% (2.2 million households) (2015)*	$\Uparrow$ There is a moderate increase in the use of electric space heating.	$\Uparrow$ There is an important growth in the use of electric space heating, mainly incentivised by the government. Probably the increase is slightly smaller in electric water heating as technologies such as solar thermal are normally not used for space heating.	$\Uparrow$ There is a slow increase in the use of electric space and water heating systems.	$\Uparrow$ | $\Downarrow$ The general trend is a slight decrease in the use of electric space and water heating systems. However, it increases within the rich.

A table similar to this one with all the indicators from DRC can be found within the electronic data or downloaded in (DRC, 2012a), and a list of all the indicators in DRC can be found in Appendix A.

N/A stands for not applicable.

4.4.1 Justification and choice of indicators

The development of the indicators' characteristics for future scenarios is, obviously, not an exact science. However, when the premises of the scenarios are set, there is not much room for discrepancies if one wants to construct internally consistent scenarios —*i.e.* scenarios where the characteristics described by the indicators are in line and do not contradict each other— which are logically reasoned and derived from the literature. The exact value of one indicator and/or its description may vary slightly, but the idea it transmits should be very similar. All the more when one is not constructing scenarios from scratch but only adding a few new indicators to them.

It seems valuable to justify here the choice of indicators developed, and why other maybe relevant indicators have not been developed. For this reasoning one has to take into account the aim of this work: extend the characteristics of the scenarios from DRC to facilitate the study of the future energy demand in the residential sector of UK.

With this aim in mind, one can see that, for example, 'Adoption of domestic (or community) microgeneration', is a relevant indicator. It is so because, although microgeneration may not influence the amount of energy that is consumed within the dwelling —at least directly—, it does greatly affect the amount and pattern of the electricity which it is demanded from the grid, and may influence the pattern of energy use in the dwelling (*e.g.* using specific appliances when there is self-generated energy available). Similarly, domestic energy storage has an effect on the pattern of energy demanded from the grid (it could potentially help decrease peak demand) and, at the same time, on the total amount of energy consumed —as storage efficiency is far from 100%—. Yet, the way energy is consumed within the dwelling is not directly influenced. A key factor for not including this indicator here has been the infancy of storage technologies, which would have made the analysis of their future evolution too uncertain.

In a similar domain, adoption of electric vehicles will greatly affect the electricity demand of households. Introducing an indicator taking it into account could seem very important, especially alongside domestic microgeneration and storage. What electric vehicles do, however, is to transfer energy consumed for transport to the household electricity demand. What this study is interested in, is on how the nature of dwellings and the households that use them influence their energy demand, not on factors that are external to the dwelling as such —as would be the case with electric vehicles—.

Other indicators could have considered the presence or not of a conservatory in the dwelling, the tenure, or the adoption of smart metering, for example, but they were not short-listed for various reasons. Conservatories influence the energy demand of households but, although they have the potential to decrease it, they are associated with an increase in energy consumption (Huebner, Hamilton, Chalabi, et al., 2015; Huebner, Hamilton, Shipworth, et al., 2015). However, due to the lack of information about conservatories, 'Type of building' and 'Energy efficiency of building and urban morphology' have been used as proxy to take their effect into consideration. On the contrary, tenure would have been a proxy for other indicators like 'Energy efficiency of buildings and urban morphology' (from DRC) and 'Dwelling area per occupant' (developed here), which are already explicitly covered; therefore, it was not selected. And, although smart metering has the potential to influence the energy demand of households, its effects depend greatly in details (appropriate forms of interface, feedback, narrative, and support (Darby, 2006)) which are difficult to take into account, and it is not clear its long-term efficacy.

Instead, 'Use of electric space (and water) heating' was included. This is because although using one fuel or another may not greatly affect the total energy demand in the household, it greatly affects how much of each type of energy is used. This is of great importance as space (and water) heating is the main source of energy consumption in dwellings (Palmer & Cooper, 2013). This fact, suggests also another very important factor which is not explicitly taken into account, which is the temperature at which homes are kept in winter. This factor lays, however, in the broad 'Attitudes to energy efficiency and sustainability' and is adjusted by 'Energy poverty'.

Other factors like the use of cooling systems would give interesting information —as climate is expected to heat up in UK— but may not be appropriate in this context. This is because they are currently very uncommon in UK, and the scenarios which this work complements do not include climate change (Lombardi et al., 2012).

4.5 Indicators' derivation and expanded information

This section shows the derivation of the different indicators. It includes the justification or definition of each new indicator, along with the question it answers and an extended version of its baseline (not available for all indicators, as the short version of the baseline often suffices). In addition, a short review of the context of the new indicators for each scenario —extracted from the sources shown in Table 4.3.0.1— was written when it was useful for their derivation (Table 4.5.0.1). It is recommended to have this section at hand when using the results table.

Table 4.5.0.1: Review and context: short description of the context of new indicators for each scenario (continued on next pages).

UK urban NSP	UK urban PR	UK urban MF	UK urban FW
Adoption of domestic (or community) microgeneration			
Community energy generation units are widely adopted. There are polices encouraging microgeneration, the public has the willingness and the information to adopt it and the total energy demand in households decreases sharply due to better dwellings and better use by occupants.	On-site generation is cheap, electricity is relatively expensive and government incentivises clean energy and promotes community microgeneration stations. People are not particularly inclined to adopt microgeneration, but it is profitable; therefore, there is a wide penetration. Buildings are generally better insulated.	On-site generation is not too cheap, but high energy prices stimulate the uptake of domestic microgeneration by those who can afford it. Buildings still consume a lot of energy; therefore, although on-site microgeneration increases, the percentage of domestic energy met by it is much less than in NSP and PR.	Rich: high energy prices make it favourable for them to install microgeneration devices as in MF. Poor: they cannot afford individual microgeneration devices, but in cases where communities are on good terms and not too poor, they manage to install community energy generators.
Adoption of domestic (or community) microgeneration			
There are more people living together, sometimes as cohousing and sometimes with friends, extended family or other families. The dwelling density increases because, although flats/apartments may be slightly larger than today, they are still smaller than current average terraced and detached houses, and many choose higher-quality but smaller homes. However, the number of very small dwellings decreases due to a decreased interest in living alone and the almost non-existence of poor people.	As current individualistic trends continue, there is a trend towards smaller household sizes (people do not want to share accommodation). It is common to divide large houses into two to accommodate to the market and newly built dwellings tend to be smaller flats rather than larger houses.	There is a trend towards smaller household sizes, as people do not want to share accommodation. At the same time, as the affordability of housing decreases, there is more substandard housing. There is a high disparity in urban dwelling density; in high income zones, there is a prevalence of houses, while, in low-income zones, there is a prevalence of flats.	The rich live in a similar way to the current (or MF) upper 10 or 15%. A large part of the poor who can afford to live in formal developments have to share their dwellings with other families. Most of those who do not share their dwelling do so only because they have been able to divide it or because the dwelling is already very small. There are plenty of informal developments. The trends seen in MF are here exacerbated.

Table 4.5.0.1 – *Continued from previous page*

UK urban NSP	UK urban PR	UK urban MF	UK urban FW
Average number and frequency of use of electric appliances			
Larger households and the will of the society make sharing home appliances the norm. More engaged and sustainable society also has the effect of reducing the superfluous use and ownership of appliances.	Households tend to be slightly smaller than those today; therefore, appliances are shared by fewer users. People's search for novelty and status continues mostly unchanged; therefore, the ownership and use of appliances increases slightly.	Households are smaller; there is less interest in sustainability and more consumerism (the amount of appliances increases until 2025). Lower earners may not be able to afford all the appliances that they would like to have, but this does not counteract the general trend.	Rich: the situation is similar to that of the top 20% in MF. Poor: they cannot afford much. Most of them have fewer appliances than they need —if they can afford to own some—. Sharing, repairing, reusing, repurposing and recycling appliances are the norm.
Energy poverty			
Better housing insulation, increase in gross domestic product (GDP) per capita, decrease in income inequality and increase in public service spending greatly reduce the risk of energy poverty. The government helps financing community or on-site microgeneration if needed. The extremely few instances of energy poverty can count on the community to alleviate their problem.	Better housing insulation and increase in GDP per capita decrease energy poverty. The state provides better insulation, domestic energy generation and energy tax discounts if needed. Lower gas prices also help decrease fuel poverty.	Housing insulation is similar to the current situation with no better use of the sun. Although GDP increases substantially, the gap between the rich and the poor also increases, leaving a large portion of society at risk of fuel poverty. The moderate increase in energy prices (in comparison with that of GDP) leaves "only" lowest earners and those living in particularly badly insulated dwellings in energy poverty. The government cannot help mitigate it, as it has to spend a lot on other issues (such as health).	Obviously there are no energy-poor among the rich. The poor, however, are virtually all energy poor —although the definition of energy poverty partially brakes in this case, as it is difficult to define "required fuel costs" for those who live in informal developments—. Those who live in formal developments struggle with high energy costs and low building standards. Burning (coal, wood etc.) is the main source of heat.

Table 4.5.0.1 – *Continued from previous page*

UK urban NSP	UK urban PR	UK urban MF	UK urban FW
Energy prices (domestic)			
In this scenario, the general amount of energy consumed is approximately one-third lower than in PR and it is mostly in the form of electric energy as well. The share that comes from renewable sources is only slightly higher than in PR. This means that the electricity price will be moderately higher than in PR, as prices will lower more slowly (lower increase with the same learning factor implies slower price reduction). The gas demand is around 25% lower, which will decrease its price even further.	An increase (peaking in 2030 at 18.51+ p/kWh) and a subsequent decrease in the electricity price are expected. This is due to the introduction of renewable energy sources, which are more expensive at the beginning. However, their price then decreases rapidly due to the high learning factor, particularly for photovoltaic and concentrated solar power. In fact, in 2050 the energy from renewable sources is generally cheaper than that which comes from fossil fuels (Greenpeace, 2015). However, the lack of demand reduces the gas price.	Increasing prices of fossil fuels (the more depleted they are, the more expensive to obtain more of them), the low uptake of renewables (slowing price reduction due to the learning factor) and the increased use of nuclear power make electricity prices increase steadily. The increasing prices of fossil fuels also affect gas prices.	In this scenario, the general amount of energy consumed is approximately 10% lower than in MF and its sources are very similar, with a slight decrease in oil and gas in favour of coal, nuclear energy and biomass. In this case, biomass is not used to generate electricity; instead, it is used by the poor as a source of heat and for cooking. The same is probably true for the increase in coal. The further increase in nuclear share affects the electricity price, making it slightly more expensive than in MF. The gas demand is lower than in MF, and its price is lower too.

Table 4.5.0.1 – *Continued from previous page*

UK urban NSP	UK urban PR	UK urban MF	UK urban FW
Type of building			
There is a decrease in land use and an increase in urbanisation and in the amount of green space. This leads to higher dwelling densities. There are fewer dwellings built than in other scenarios due to the high adaptation of the current stock. Current trends increasing the proportion of flats are exacerbated, and there are very few new (semi-)detached houses constructed. Construction of terraced houses stays similar. Green space may be gained where there were old single-family houses with gardens, in particular (semi-)detached houses. Community feeling drives a decrease in the demand for privacy.	The percentage of new buildings remains similar, with a decrease in detached houses in favour of terraced. This increases the dwelling density due to the high percentage of new flats constructed (mainly in city centres) and lower percentage of (semi-)detached houses. However, there is high adaptability of the existing stock, which decreases the amount of new buildings in relation to other scenarios. Terraced and (semi-)detached houses are still in high demand, as people seek privacy.	In highly popular and in lower-income neighbourhoods, there is a high increase of flats, while, in high-income neighbourhoods, what increases is the presence of new (semi-)detached houses. This scenario presents a strong "type of building polarisation". Moreover, the replacement levels are high; therefore, there are more buildings built than in other scenarios.	There is an overall decrease in dwelling density, but the polarisation between the rich and the poor is extreme in this scenario. The rich live mainly in detached and semi-detached houses, except in popular zones, where there is a good provision of high-profile flats too. The poor inhabit previously built flats and, in some regions, terraced houses (normally shared between several families). In formal developments, new flats are the only new construction. In informal developments, dwellings are more similar to shacks than to proper buildings.

Table 4.5.0.1 – *Continued from previous page*

UK urban NSP	UK urban PR	UK urban MF	UK urban FW
Use of electric space (and water) heating			
Although there is a stronger decrease in GHGs produced by household heating than in PR (and electricity is clean), the uptake of electric space and water heating is lower here. The reason is that there is a much greater increase of district heating and other forms of dwelling heating technologies that use the sun's and the earth's heat.	Although gas is cheap, as the government is leading a transition to clean energy sources, it incentivises district heating when feasible (often geothermal) and electric heating otherwise —which is the option preferred by the population—. The combination of microgeneration and electric heating is particularly appealing for customers. Other heating technologies such as solar thermal also have their role in order to replace gas for heating (mostly water).	Proportionally, the increase in gas price is much higher than that of electricity. This will increase the installation of heat pumps in new buildings and when systems need to be changed. Those who have on-site energy generation will also prefer electric heating.	Rich: similar to MF but probably slightly larger, as nuclear energy seems to be preferred over other sources of energy such as gas. Poor: they are mostly energy poor; therefore, this decreases their use of electric heating. They mostly use biomass or coal for heat.

4.5.1 Adoption of domestic (or community) microgeneration

Definition/justification: microgeneration partly avoids the need to demand energy.

Question: what's the percentage of domestic energy consumption met by microgeneration?

Baseline UK: in 2016, consumption of self-produced electricity by the domestic sector was 1356 GWh, which accounts for 1.3% of all domestic consumption (Department for Business Energy and Industrial Strategy [BEIS], 2012), with a total capacity of 2.55 GW (Office of Gas and Electricity Markets [Ofgem], 2017). The total capacity of community installations was about 0.23 GW (Ofgem, 2017), accounting for ~0.1% of consumption. In 2010, the total installed microgeneration capacity (including commercial and industrial) in the UK was almost zero.

Review and context: see Table 4.5.0.1.

4.5.2 Attitudes to energy efficiency and sustainability

Justification/definition: this indicator does not measure intentions but results; therefore, it includes education, as well as personal preferences, habits and social trends. Intentions do not always match results, partly due to the lack of knowledge, difficulty of changing habits (Huebner et al., 2013; Huebner, Hamilton, Shipworth, et al., 2015) or the social environment making it difficult.

Question: what are the general attitudes, knowledge and ease to act in a sustainable way of the population?

Baseline UK (2018): lack of sustainable alternatives and of simple, coherent and relevant information (Nuttall & Shankar, 2017; The Guardian, 2010). A small proportion of the population actively tries to reduce their energy consumption and to be more sustainable in general, but lack of reliable information, difficulty of doing what is needed in the current society, consumerism and social inertia make it very effort intensive. Therefore, many people tend to pick one "cause" (*e.g.* avoidance of plastics or veganism) and put most of their efforts there, more than to follow an overall "sustainable life". Moreover, despite good intentions, results are usually very poor due to misinformation, difficulty of changing habits and social inertia. In addition, for those who are the most knowledgeable, the tension between what they know they should do and what they can actually do can even lead to paralysis (Longo et al., 2019).

4.5.3 Average dwelling (usable) floor area

Justification/definition: larger dwellings tend to consume more energy (Wright, 2008). Also, together with 'Average household size', it gives information on the average number of occupants per usable area that dwellings have (see Section 4.5.5), which relates to the amount of energy used in dwellings.

Question: how much floor area do dwellings have in comparison with the baseline?

Baseline UK (2013): mean total usable floor area of 95 m^2; 9.4% have smaller than 50 m^2 of internal floor space, 24.9% have at least 110 m^2 of internal floor space (Department for Communities and Local Government [DCLG], 2015) (number of dwellings in the UK (2013): 23.3 million).

Review and context: see Table 4.5.0.1.

4.5.4 Average number and frequency of use of electric appliances

Justification/definition: "Electrical appliances make a very significant contribution to a household's electricity consumption. This impact not only relates to the number of each type of appliance owned, but also to the power demand and frequency of use" (Jones et al., 2015, p. 12 (912)).

Question: what is the pattern of household appliance use in the scenario?

Baseline UK (2011): from the report by Hulme et al. (2013):

– Laundry appliances: washing machines in 97% of households. Median use four times a week at 40°C or less. Tumble dryers in 67% of households. Median use three times a week in winter; few use them in summer.

– Refrigeration appliances: refrigerators in 99% of households (can be combined with freezers). Freezers in 93% of households.

– Dishwashers: in 41% of households. Median use four times a week.

– Cooking appliances: around 38% of households have electric hobs, around 70% have electric ovens and around 80% have microwave ovens. Use is not determined but the survey by Statista (2017) shows how often people cook food from scratch: once/few times a day, 34%; few times a week, 31%; once a week, 11%; once/few times a month, 7%; less often, 9%; never, 9%.

– Information and communication technologies and home entertainment: median number of televisions in homes is two; the most used one runs 5–6 h/d. No concrete data for other appliances, but different sources show an increase in sales (Statista, 2019) and in appliance energy use (Palmer & Cooper, 2013) in the last years.

Review and context: see Table 4.5.0.1.

4.5.5 Dwelling area per occupant

Justification/definition: it relates to the amount of energy used in dwellings; a higher density of occupants means less space heating per person and a higher likelihood of sharing consumer items (Bhattacharjee & Reichard, 2011).

Question: what is the average area per occupant in dwellings?

Baseline UK (2011–2013): average household size (2011): 2.3 (Office for National Statistics [ONS], 2013) (the indicator in DRC shows 2.4, which is the value from 2001). Average dwelling (usable) floor area (2013): 95 m^2. The result is one occupant every 41.3 m^2.

4.5.6 Energy poverty

Definition: "Fuel poverty in England is measured using the “Low Income High Costs” indicator, which considers a household to be fuel poor if: (1) they have required fuel costs that are above average (the national median level); (2) were they to spend that amount, they would be left with a residual income below the official poverty line" (BEIS, 2017a, p. 3).

Question: what is the percentage of population in energy poverty?

Baseline UK (2015): around 11% (approximately 2.5 million households) (BEIS, 2017a). It has been fluctuating by less than 2 percentage points since 2003, between more than 10% and less than 12%. The average fuel poverty gap (average reduction in fuel bill needed to remove a household from fuel poverty) in 2015 was £353, which has been slowly decreasing since peaking in 2012 after at least 10 years rising.

Review and context: see Table 4.5.0.1.

4.5.7 Energy prices (domestic)

Definition: average UK domestic energy price (including taxes) for a medium customer for a given year.

Justification: the price of domestic energy can influence the energy demand of households, particularly those with low income (BEIS, 2017a). This effect may be amplified if energy prices and energy consumption are made visible and may be used to decrease peak demand —by changing energy pricing depending on the time of the day (Darby, 2006)—. It is expected that an increase in energy prices would incentivise adoption of on-site generation (Jager, 2006).

A forecast of the future energy prices is outside the scope of this research. However, the relative differences between scenarios and a rough relation to current values are what can be evaluated.

Question: what are the average energy prices of domestic energy (electricity and gas) for a given year?

Baseline UK (2016): average for medium consumers, 2016: electricity price: 15.47 p/kWh (2012: 14.05 p/kWh); gas: 4.31 p/kWh (2012: 4.46 p/kWh) (BEIS, 2018b).

GSG used the *Energy [R]evolution* reports by GreenpeaceEREC (2007, 2008) to help generate energy-related data in their scenarios. These reports portray a reference scenario (Ref) and an Energy [R]evolution scenario (E[R]), which are broadly compatible with MF and PR, respectively. In more recent reports, another scenario is added, advanced Energy [R]evolution scenario (AE[R]). This scenario is, however, not compatible with any of the other scenarios used in DRC. Reproductions of the figures and tables used to characterise this indicator can be found in Appendix B. They belong to three sources: (1) the latest *Energy [R]evolution* report by Greenpeace (2015) (figure 6.4.6 and table 5.4; the figure shows the development of the electricity generation costs in Ref, E[R] and AE[R] for OECD Europe; the table shows the projections for fossil fuel and biomass prices for different parts of the world until 2050); (2) the technical document of the GSG's scenarios by Electris et al. (2009); figure 3-44, which shows the electricity generation shares in 2050 in MF and PR compared to those in 2005); and (3) the table generator tool by Tellus Institute (n.d.-a) (which shows the values for different Western Europe scenarios of selected indicators in different points in the future).

Calculations of final electricity prices in Ref and E[R]

(based on information given in figure 6.4.6 by Greenpeace (2015); see Figure B.0.0.2 in Appendix B)

What is relevant here is the rough evolution of the electricity prices. For that, it is assumed that they are proportional to the electricity generation costs and that this proportionality will not change in time. It is also assumed that taxes stay constant. With these assumptions, the relation between the price of UK domestic electricity and the electricity generation costs in 2012 is the same as the relation between the electricity prices and generation costs in 2050 (for the different scenarios). Therefore, a simple cross-multiplication can be used to derive the final electricity prices in Ref and E[R] by measuring the relative increases in electricity generation costs in the figures. This leads to:

- Final electricity price in E[R]: 15.25 p/kWh (with a maximum price in 2030 of 18.51 p/kWh).
- Final electricity price in Ref: 17.36 p/kWh.

Both GSG and Greenpeace assume a decrease in the use of nuclear energy in the electricity mix of Europe (their definitions of the area are not exact but similar). The UK, however, seems to go in the opposite direction despite the increases in electricity costs that this implies (BEIS, 2017b; HM Government, 2013). The narratives of the scenarios suggest that this increase will be higher in Ref/MF (17.36++ p/kWh) than in E[R]/PR (15.25+ p/kWh).

Calculations of final gas prices in Ref and E[R]

(based on the information given in table 5.4 by Greenpeace (2015); see Figure B.0.0.3 in Appendix B)

The procedure here is similar to that used with the electricity prices; the price for UK domestic gas in 2012 is defined as proportional to the value for Europe in 2012/2013 shown in the table, and with a cross-multiplication the price for 2050 is obtained:

– Final gas price in E[R]: 3.54 p/kWh.

– Final price in Ref: 6.21 p/kWh.

Review and context: see Table 4.5.0.1.

4.5.8 Type of building

Justification/definition: although it is expected that in OECD member countries approximately 75% of the 2013 building stock will still be standing in 2050 (IEA, 2013) and that in the case of UK more than two-thirds of the 2050 housing stock was already built in 2005 (Boardman et al., 2005), the remaining stock will have an impact on both direct energy consumption (*e.g.* blocks of buildings use less energy than detached houses) (Bhattacharjee & Reichard, 2011; Jones et al., 2015; Jones & Lomas, 2015) and the heat island effect (gardens help mitigate heat island effect; blocks of buildings increase it) (U.S. Environmental Protection Agency, 2008).

Question: what is the composition of the domestic building stock?

Baseline UK (2013): end terrace, 10.4%; mid terrace, 18.8%; semi-detached, 27.6%; detached, 22.6%; flat, 20.6% (DCLG, 2015). For newly built: end terrace, 10.3%; mid terrace, 12.9%; semi-detached, 11.0%; detached, 23.7%; flat, 42.2% (DCLG, 2015).

Review and context: see Table 4.5.0.1.

4.5.9 Use of electric space (and water) heating

Justification/definition: heating (space and water) is the largest slice of UK household energy use (around 60% and 20% respectively) (Palmer & Cooper, 2013); therefore, the number of dwellings using electric heating has a huge impact in the electricity network's load. "In almost all cases, households that use electricity for space heating also use electricity for water heating" and "the vast majority of households that use electric water heating also use electricity for space heating" (Ofgem, 2015, p. 12). Therefore, it does not make sense to separate space and water heating into two distinct indicators.

Currently, electric heating is not common in the UK and is more expensive than gas heating. However, it is expected to grow with the popularisation of heat pumps, as they are more efficient than other types of electric heating and still are a minority in the UK ("typically, heat pumps can produce from 2.5 to 4 times as much useful heat as the amount of high-grade energy input, with variations due to seasonal performance" (Greenpeace, 2015, p. 281). The adoption of microgeneration and the preference for electricity in sustainable scenarios (where the grid is decarbonised) should also push in this direction.

Question: what is the percentage of households using electric space (and water) heating?

Baseline GB (2015): 8.5% (2.2 M households) (Ofgem, 2015).

Review and context: see Table 4.5.0.1.

4.6 Case study

The indicators and characteristics developed in this chapter have been conceived to enable the projection into future scenarios of disaggregated household energy demand data. However, they can be used seamlessly with DRC. To demonstrate that, DRC is used with these additions to evaluate the resilience of one of the recommendations of the Swedish measurement campaign (Zimmermann, 2009) mentioned in Section 2.1: the implementation of a ban to appliances with standby power above 0.5 W.

The *Urban Futures Method* consists of four steps: (1) identify a 'solution – benefit' pair, (2) identify the necessary conditions for the 'solution – benefit' pair to work, (3) determine the performance of the necessary conditions in each scenario, and (4) determine the resilience of the pair in the future. With this information, one can decide whether to implement the solution, improve it, or consider an alternative solution. For more details about the *Urban Futures Method*, see the book by Lombardi et al. (2012), the paper by Rogers et al. (2012), or their interactive tool (DRC, 2012b) —which is designed to guide the user in the process of the *Urban Futures Method*—.

The benefit of the solution chosen is to decrease the electricity consumed in households. Therefore, the 'solution – benefit' pair is 'implementation of a ban on appliances with standby power above 0.5 W – decrease the electricity consumed in households'. Now, the societal, technological, economical, environmental, policy and organisational conditions that enable the solution to keep functioning so it delivers its intended benefit have to be identified (STEEPO analysis). These are:

(a) Appliances must be used.

(b) Users must use the standby mode.

(c) Governments must be able to enforce the ban.

(d) Policy must be maintained despite changes in the government.

To determine the performance of these necessary conditions in the future scenarios, they are analysed against the relevant indicators (those from DRC can be found within the electronic data provided, or using the DRC interactive tool (DRC, 2012b)). The grade to which each necessary condition is likely to perform for each indicator in each scenario is judged (highly likely, at risk or highly unlikely) and synthesised in few words. This leads to a grid reviewing each condition's grade for each scenario. Such grid helps determine whether the solution continues to deliver its intended benefit in each future scenario or not, and identify its vulnerabilities and uncertainties it may face.

Table 4.6.0.1 shows a summary of the futures analysis for the preceding necessary conditions, showing a tick (✓) when the condition is supported in the scenario, a cross (×) when it is not supported, and an interrogation mark (?) when it is questionable if it is supported or not.

Table 4.6.0.1: Summary of the futures analysis of the conditions needed for the pair 'implementation of a ban on appliances with standby power above 0.5 W – decrease the electricity consumed in households'.

Condition	Performance			
	NSP	PR	MF	FWr|FWp
(a) Appliances must be used	✓	✓	✓	✓|×
(b) Users must use the standby mode	?	✓	✓	✓|×
(c) Governments must be able to enforce the ban	✓	✓	?	?
(d) Policy must be maintained despite changes in the government	✓	✓	?	?

✓, supported in the scenario; ?, questionable if supported in the scenario; ×, not supported in the scenario.

The characteristics of 'Average number and frequency of use of electric appliances' directly determine the performance of condition (a). To determine the performance of condition (b), the characteristics of several indicators are needed, with 'Attitudes to energy efficiency and sustainability' and 'Energy price (domestic)' being central. For the other two necessary conditions, the existing DRC covers their analysis. Therefore, without the additions presented in this chapter, a user choosing to evaluate the resilience of such a 'solution – benefit' pair would need to spontaneously infer the information used to evaluate conditions (a) and (b). This means that such evaluation would have probably been done without some of the relevant information, and this would likely cause the result to be less consistent.

The results of the analysis recommend implementing the solution because it delivers benefits in all scenarios. Its weak points are in MF and FW, where pressure from users (MF) and/or from producers (MF and FW) could lead the government to either withdraw the measure or be lax in its application; and in FW, where it is not useful for the poor. However, the application of the measure obliges producers to develop low-consuming standby modes that are appealing to users. Only if producers do not manage to do it, or the implementation of these standby modes continues to be expensive for the producers, will these benefits be jeopardised. Ironically, the fact that in NSP users usually fully stop their appliances, makes this solution less effective in this scenario. See Table 4.6.0.2 for a synthesis of the results for each scenario.

Table 4.6.0.2: Synthesis of the results of the futures analysis of the 'solution – benefit' pair 'implementation of a ban on appliances with standby power above 0.5 W – decrease the electricity consumed in households'.

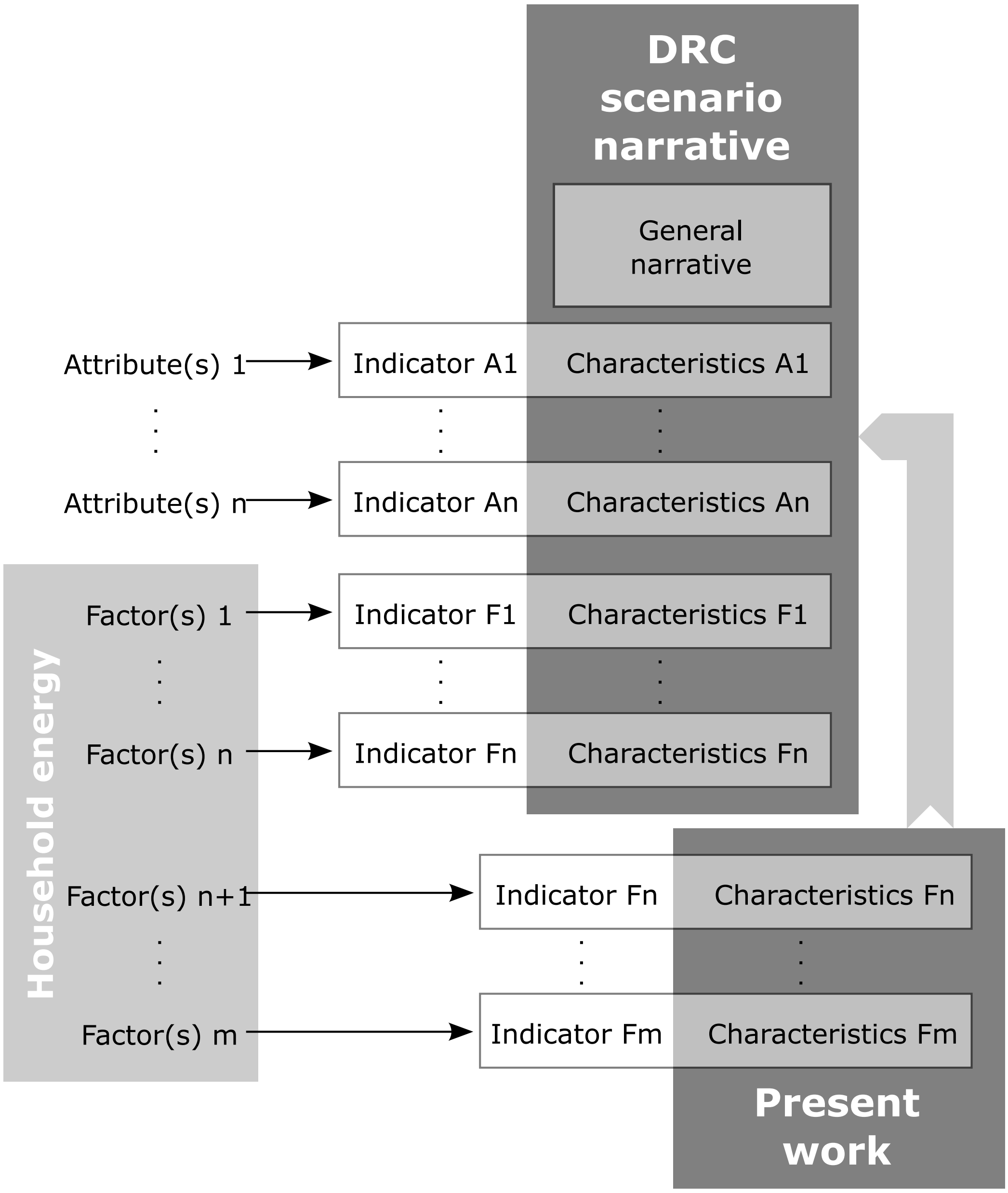
NSP	PR	MF	FW
The solution delivers its intended benefits. It does so less than in PR because it is less needed: fewer appliances are used, and they are often fully stopped instead of left in standby mode.	All conditions perform well. In this scenario, the solution is useful and needed.	This is a very useful and needed solution in this scenario. However, it is possible that it is withdrawn due to market pressures (from users or producers) or not fully enforced.	This is a useful and needed solution for the rich only, as the poor barely use appliances and turn them off when not in use. Although the government is keener than in MF in securing resources, they may make exceptions when faced with large companies.

4.7 Discussion of the process

It is important to apply futures analysis to sustainable interventions of all kinds to evaluate their resilience and decrease by design the possibility that assets become stranded while still operative. Broadening the possible uses of scenario analysis to specific domains, as done in this chapter, may help in this regard. In particular, a futures analysis of the factors determining the energy demand in households could identify a range of distinct plausible paths that this demand could take in the future, thus reducing the uncertainty faced when designing interventions, plans or regulations.

This work shows how the scenarios from DRC can be complemented and adapted to the specific needs of the user. Figure 4.7.0.1 shows it graphically: some factors affecting the energy demand in households were not characterised in DRC; a number of indicators have been defined to account for these factors and have been characterised in each scenario; now these indicators seamlessly complement the tool. A limitation of these indicators is that their base year is variable. This was unavoidable due to data availability and it translates into that the time distance between the base and the future scenarios are not exactly the same for all indicators. In any case, the variability in the base year of the different indicators is much smaller than the time distance between these bases and the projection's year, 2050.

The scenarios adapted here have an architecture —a general narrative plus the characteristics of a set of indicators (Figure 4.1.1.1)— very similar to that of a large body of scenarios developed in the literature. Therefore, this work demonstrates also how such types of scenarios could be adapted to study specific domains of interest outside the original scope of the scenario.



Some of the attributes represented by the indicators defining Designing Resilient Cities's (DRC) scenario narratives are factors determining the energy demand of households. The work done here has defined indicators to represent the missing factors determining household energy demand and characterised them to complement the scenarios from DRC.

Figure 4.7.0.1: Graphical description of the work done in this chapter and how it complements the scenarios from DRC.

As the case study shows, the generation of the new indicators presented here allows the systematic evaluation of interventions aimed at decreasing the energy consumed in households. This demonstrates again the power of futures scenarios and now that of their possible extensions to help reveal where alternative thinking may help policy and practice. The specific extension presented here allows to project into these scenarios current household energy demand data to study their evolution. It also allows, for example, to explore the evolution of different aspects related to the household energy demand in the different futures scenarios. These properties can be used to inform better regulations or interventions related to the built environment or to plan better, more resilient, energy networks to supply dwellings.

This chapter further supports the evidence from the extensive literature regarding futures scenarios, in that these are powerful tools to help think about the future. In addition, not only does it convey the additional tables of characteristics for each scenario to aid that thinking; it also trains the readers in the process of futures thinking and scenario building so that they can form their own arguments. The readers, therefore, are able to use futures scenarios and also to develop them further if necessary.

4.8 Summary and conclusions

In order for any intervention not to lose its effectiveness in the future, it is important to make sure that it is resilient regardless how the future evolves (within a range of plausibility). Futures scenarios are a good tool for helping design such resilient interventions. In particular, buildings are responsible for a significant proportion of GHG emissions and their average lifespans are very long. It is, therefore, crucial for any intervention in the built environment to deliver its desired effects irrespective of the future that arises. In addition, futures scenarios can reveal as well where alternative thinking may help improve policy for a changing future.

One tool that can be easily adapted to study the future of household energy demand is *Designing Resilient Cities* (DRC). DRC is a tool designed to study the performance of sustainable interventions in the urban environment. It adapted the four quantified scenarios from GSG (NSP, PR, MF and FW), which are explorative scenarios, to urban UK in 2050. They are sufficiently distinct and extend enough to the extremes of plausibility to cover a broad range of possible directions in which the future could unfold. Their architecture comprises a general narrative plus the characteristics of a set of indicators (see Figure 4.1.1.1 for a graphical depiction of this architecture), which is typical for the scenarios used in the futures studies.

The aim of DRC partly covers the study of the household energy demand. However, the scenarios it uses have to be adapted if a deep analysis of this domain is sought. Fortunately, the scenarios used in DRC are designed in a way that new indicators can be added to them. A method to do exactly that has been developed in Section 4.3 and is generalised in Section 8.4.1.

The factors affecting the energy demand in households are complex and interrelated. However, it has been possible to curate a set of indicators to take them into account. Subsequently, those which were not already present in DRC were characterised in the different scenarios using the method mentioned above. As shown with the case study, this set of indicators can be successfully used, together with DRC, to evaluate the resilience of interventions aimed at decreasing the energy demand in households. This can be used to improve the design of any kind of intervention in this domain, *i.e* policy related to housing or interventions aimed at decreasing the energy demand in households.

This chapter has provided new indicators adding detail about households and the way they use energy in the DRC scenarios, and demonstrated the method used to expand it. In doing so, it trains the readers in future thinking, which they can then use in other domains.

As future work, DRC could be extended to other specific domains of the urban environment. It could also be adapted to other urban environments or to take climate change into account. Another useful option would be to adapt the scenarios from the GSG to evaluate existential risks, global catastrophic risks, civilization-ending events and other risks that humanity face in order to help define the global priorities (the world's most pressing problems) that humanity should address.

Chapter 5

Development of the tool

All models are wrong, but some are useful.

— George Box

This chapter presents the tool to project disaggregated data into future scenarios. The tool comprises a mathematical framework and the method to use it. The mathematical framework is developed for the case of household electricity demand and is subsequently generalised. After that, the method to use it is explained and an example is given to illustrate the process. Finally, the details of the use of this tool are extensively discussed and a summary of the chapter and its conclusions are given.

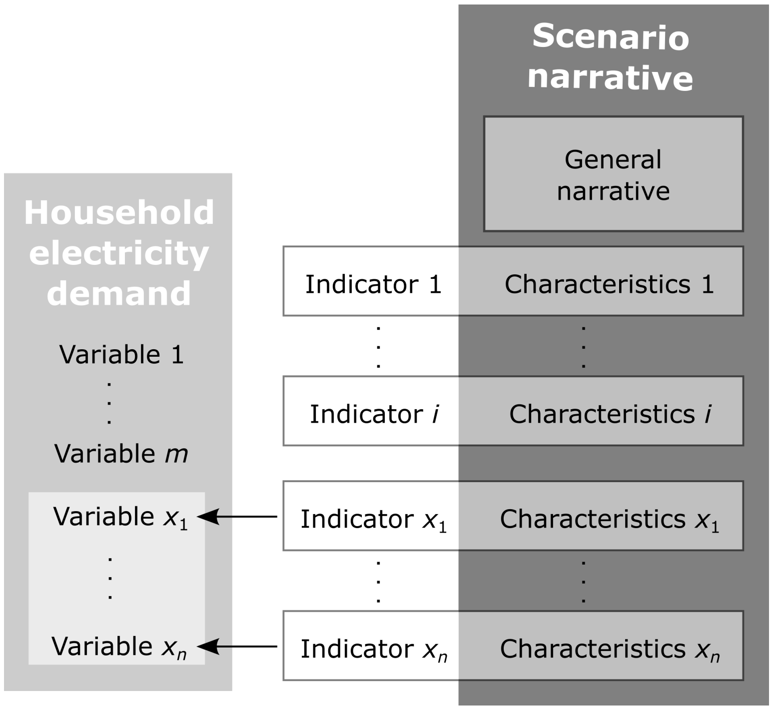
5.1 Disaggregated data and future scenarios

Methods used to obtain quantitative scenarios usually rely on historic data extrapolation and/or expert judgement (Amer et al., 2013). In some cases, however, data are projected to construct or characterise these scenarios. The tools used for such projections are usually complex and only able to project aggregated data. Therefore, the projection of disaggregated data into future scenarios with a simple method is not common.

Due to their atomised nature, disaggregated data has historically not been easy to collect. With increasingly significant volumes of data being generated at a pace which is constantly accelerating (DOMO, 2018; Peters, 2012), this is, however, changing. In particular, the growing adoption of smart metering devices and other end-user side measuring terminals (Zhou et al., 2016; Zhou & Yang, 2016) may increase the availability of household energy demand data.

A projection into a scenario is the transformation of the aggregated information held in a data set, so that it approximates the likely behaviour those data would have on the characteristics of that scenario.

Any disaggregated data is produced by an agent, and its behaviour depends on a number of variables related to the agent —*e.g.* household electricity demand data is determined by a number of household variables like household size or income level, dwelling size, type of building, etc.—. At the same time, future scenarios are usually defined by the characteristics of a set of indicators, some of which may be directly or indirectly related to these variables on which the behaviour of the disaggregated data depends. Figure 5.1.0.1 graphically shows this relation between the indicators characterising a scenario and the variables determining the electricity demand in households.



The narrative of each scenario comprises a brief general narrative describing the main aspects of the scenario and the characteristics describing the performance of a set of indicators in the scenario. In this example, the household electricity demand variables which are described by the indicators can be projected —variables $x_1 \ldots x_n$—.

Figure 5.1.0.1: Composition showing a typical scenarios narrative and how it relates to variables for which projections can be obtained.

A simple mathematical framework to project disaggregated data into future scenarios is derived in this chapter. This maximises the use of disaggregated data being generated to establish how they can help us further understand the impacts of future uncertainty and improve resilience of current solutions.

5.2 Overview and concept

For clarity, the mathematical framework to project disaggregated data into scenarios is developed using the specific example of disaggregated household electricity demand data. However, these data are not special in any way nor have they distinct properties than other types of disaggregated data. Therefore, the method is afterwards effortlessly generalised to any kind of disaggregated data. It is assumed that the data come with metadata giving information about the features and demographics of the households which generated them. Without these metadata it is generally not possible to perform a projection.

The projections are obtained for mean values, *i.e.* the average electricity demand per household. However, the starting point for developing the framework is the total electricity demand of the household population in the data set. This population can be broken down into groups of households sharing the "value" of a given variable. For example, the "values" for the variable 'Type of building' would be 'Bungalows', 'Detached houses', 'Apartments', etc.; and for the variable 'Dwelling insulation' they could be, for example, 'Very poorly insulated', 'Poorly insulated', up to 'Extremely well insulated'. Each of these households groups has a particular average demand of electricity. Therefore, the total electricity demand of the household population can be found by multiplying the number of households in each group by their average electricity demand and adding up for all groups. It is clear that if a scenario does not change anything, neither does its total electricity demand. However, if a scenario changes the number of households in the different groups, the average electricity demands of the groups will still not change (*e.g.* the average electricity demand of 'Extremely well insulated' dwellings is still the same), while the total electricity demand across the whole population will change, see Figure 5.2.0.1.

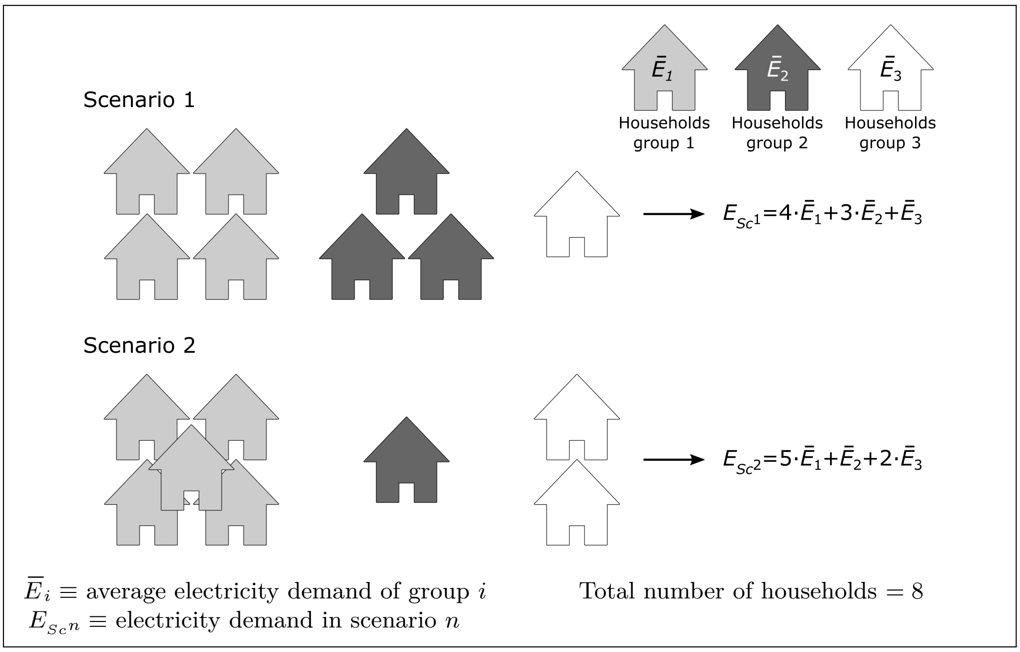


Figure 5.2.0.1: Sketch of the tool's concept.

Now, if the total electricity demand is divided by the number of households in the scenario, the overall average electricity demand per household is found. When the same is done at the other side of the equation, the ratio of households each group represents is obtained (*e.g.* the number of bungalows over the total number of dwellings). The resulting expression for Scenario 1 in Figure 5.2.0.1 would then be:

$$\overline{E}_{Sc1} = \frac{1}{2} \cdot \overline{E}_1 + \frac{3}{8} \cdot \overline{E}_2 + \frac{1}{8} \cdot \overline{E}_3$$

This simple concept is the basis for the tool. In summary, it finds the average household electricity demand for a given scenario by making the ratios of the groups match the characteristics that the given variable shows in the scenario. This is only a partial approximation to the average household electricity demand in the scenario, as it only accounts for the effects that varying one variable has on this demand. However, this same procedure can be repeated, separately, for as many variables as needed and aggregated to obtain a much more complete approximation of the average electricity demand per household in the scenario.

5.3 Introducing the formalism

A household's demand for electricity depends on a number of variables (income, type of building, household size, dwelling size, etc.). Therefore, this demand can be represented as a function of these variables. Let's call this function E and the different variables $x_1, x_2, \ldots, x_n$. Then it can be expressed:

$$E(x_1, x_2, \ldots, x_n) \tag{5.1}$$

Sets of scenarios are normally developed together. The usual set of scenarios is formed by a base/reference scenario which corresponds to a specific environment at a specific point in time (typically the present when the scenario was developed), where all the characteristics are known, and some —usually four— scenarios corresponding to the same environment in distinct futures. These scenarios are typically described by a general narrative and the characteristics of a given set of indicators, which is the same for the whole set of scenarios. The differences in the characteristics of these indicators and the general narrative is what differentiates the scenarios. These indicators can be very varied. Some are not related to electricity, residential buildings, or their occupants, but some are directly or indirectly related, or sometimes equivalent to the variables mentioned before. These indicators define the variables for which disaggregated data can be projected into the future scenarios (see Figure 5.1.0.1).

Then, the electricity demand of the housing sector in a given scenario can be expressed as the value of the function in Expression 5.1 when the variables follow the characteristics of the scenario:

$$\begin{aligned} E^B &= E(x_1^B, x_2^B, \ldots, x_n^B); \\ E^1 &= E(x_1^1, x_2^1, \ldots, x_n^1); \\ E^2 &= E(x_1^2, x_2^2, \ldots, x_n^2); \\ &\ldots \\ E^{Sc} &= E(x_1^{Sc}, x_2^{Sc}, \ldots, x_n^{Sc}) \end{aligned} \tag{5.2}$$

Where E^B is the household electricity demand in the base scenario, E^1, E^2 and E^{Sc} are the household electricity demands in the future scenarios, and x_j^{Sc} are the values of the variables in the scenarios.

However, projecting household electricity demand data into the different scenarios as a function of all the variables at once would require a simulation taking into account all the interconnectivities and feedback loops between them. When the scenarios have been developed using computer models coupled with historical data and trends, this can normally be done at a macro level, therefore for aggregated data (*e.g. PoleStar* or *Pymedeas models* are *Integrated Assessment Models* (IAM), which are developed with the aim of generating coherent future scenarios to obtain information of certain aggregated or partially aggregated variables (MEDEAS, n.d.; Tellus Institute, n.d.-b). However, in order to do it with disaggregated data, the level of interconnection of the model would need to be unrealistically high. Therefore, the approach taken here is much more modest: it obtains the projection for one variable at a time. This means that one can obtain $E^{Sc}(x_n^{Sc})$, the projection of the household electricity demand in scenario Sc produced by the evolution of variable x_n^{Sc} in the scenario while keeping the other variables constant (a_u); therefore one could obtain the following projections:

$$\begin{aligned} &E^1(x_1^1) = E(x_1^1, a_2, \ldots, a_h); \ \ldots\ ; E^1(x_h^1) = E(a_1, a_2, \ldots, x_h^1); \\ &E^2(x_1^2) = E(x_1^2, a_2, \ldots, a_h); \ \ldots\ ; E^2(x_h^2) = E(a_1, a_2, \ldots, x_h^2); \\ &\ldots \\ &E^{Sc}(x_1^{Sc}) = E(x_1^{Sc}, a_2, \ldots, a_h); \ \ldots\ ; E^{Sc}(x_h^{Sc}) = E(a_1, a_2, \ldots, x_h^{Sc}) \end{aligned} \tag{5.3}$$

Therefore, one condition for the projections is that the variables being projected are characterised in the scenarios. At the same time, in order to obtain a projection for a given variable, the household population in the future scenario, in the data and in the base scenario have to be described by the same groups. The environment from where the data come and the base scenario are typically the same or similar and no issues arise. However, if the future scenario is too different it might be impossible to describe its household population with the same groups. In these cases, this scenario is too disruptive to project the data for the given variable. Projections are independent from each other and depend on the particular characteristics of each variable in the future scenario. Therefore, one scenario might be too disruptive to perform a projection for a given variable but still be perfectly suitable to project a different variable.

One advantage of this method is that the contributions of each variable to the electricity demand of the scenario are visible. The combination of the different projections into an aggregate for each scenario depends on the relationship between variables. These relationships clearly differ for data in different domains, but they also differ between scenarios —*e.g.* in one scenario a given variable may have much larger influence in the household electricity demand than in another scenario—. Finding a method to aggregate projections is outside the scope of this chapter and of the thesis as a whole.

5.4 Mathematical framework

The general principle to obtain $E^{Sc}(x_n^{Sc})$, is to use a ratio-weighted sum. In addition, an extension of this method to include simple corrections to the projections is subsequently explained. The ratio-weighted sums account for the variations in the distribution of households with respect to a certain variable which follows the characteristics of a scenario. The corrections are modifications to the amounts of the electricity demand conveyed by the data (*i.e.* a percentage of increase or decrease applied to the value of each data point).

One may be interested in projecting a single variable, a subset of variables or maybe all the variables in a domain. Some variables are described by a single indicator, some by a group of indicators, and sometimes indicators describe more than one variable. Due to this range of possibilities, it is important to precisely define the variables for which projections are sought before attempting the projections themselves. In this process the indicators whose characteristics describe the variables are found and coupled to the variable(s) they describe. Then, one projection has to be attempted at a time. For each projection, the metadata have to be reviewed to find household information about the variable. Sometimes the metadata do not provide direct information about the variable, or the inputs they provide are poor or need to be adapted. When no direct information about the variable is available in the metadata, a proxy may be used instead (*e.g.* use number of bedrooms as proxy for size of the dwellings).

Once the variable of interest is defined, the indicator(s) describing it identified and the metadata information ready for use, the groups can be defined. For example, for the variable 'Type of building', the households in the data set would be grouped according to the dwelling's building type, and for the variable 'Income inequality', the social class they belong to (social classes A, B, C1, C2, D or E) could be used as proxy. If, following the nomenclature defined earlier these variables are called x_1 and x_2 respectively, the groupings can be expressed in the following way:

$$
\begin{aligned}
\{x_1\} &= \{\text{apartment, terraced, semi-detached, detached, bungalow}\} \\
\{x_2\} &= \{\text{A, B, C1, C2, D, E}\}
\end{aligned}
\tag{5.4}
$$

Then, the total electricity demand as a function of the variable x_n for a given period of time, $E(x_n)$, is expressed as the sum of the electricity demand in each group of x_n:

$$
E(x_n) = \sum_{j=1}^{i} E_j = E_1 + \ldots + E_i \tag{5.5}
$$

where E_j are the electricity demands of each group for variable x_n. For example, in the case of 'Income inequality', which we called x_2, the previous expression would be:

$$
E(x_2) = E_A + E_B + E_{C1} + E_{C2} + E_D + E_E \tag{5.6}
$$

where E_A is the electricity demand of the group social class A, and the other terms are the same for the groups social class B, C1, C2, D, and E.

When considering the base scenario, $E^B(x_n^B) = E^B(x_m^B) = E^B$, which is the total electricity demand in the given period of time. The only thing that changes is the variable used to define the groups; *i.e.* in the base scenario it is the same to express the total electricity demand by adding up the electricity demand from all types of dwellings, or by adding up the electricity demand from all social classes. See subsequent Figure 5.4.0.1 for a general case (this figure shows the average across the population instead of the total electricity demand, but the principle is the same).

As this method deals with each $E(x_n)$ separately and to make the notation simpler, from now on the variable on which the electricity demand depends, x_n, is going to be omitted, *i.e.* $E^B(x_n^B) \equiv E^B$. Now, and in general for the formalism, unless otherwise stated, any symbol with sub-index indicates that it is relative to a group, and without sub-index that is relative to the whole population (*e.g.* E is total electricity demand while E_j is the electricity demand of group j). Following this notation, the expression for the electricity demand in the base scenario is the following:

$$
E^B = \sum_{j=1}^{i} E_j^B = E_1^B + \ldots + E_i^B \tag{5.7}
$$

Now, E_j^B (the electricity demand of each group) can be expressed as the group's average electricity demand per household, $\overline{E}_j^B$, times the number of households in the group, N_j^B; that is:

$$
E^B = \sum_{j=1}^{i} N_j^B \cdot \overline{E}_j^B = N_1^B \overline{E}_1^B + \ldots + N_i^B \overline{E}_i^B \tag{5.8}
$$

However, the metadata give information about the agents producing the data, in this case the households. Therefore, what is relevant for the framework is the average electricity demand per household across the whole population, $\overline{E}^B$, rather than the total electricity demand. This is easily found dividing E^B by the total number of households, N^B:

$$\overline{E}^B = \frac{E^B}{N^B} = \frac{1}{N^B}\sum_{j=1}^{i} N_j^B \cdot \overline{E}_j^B = \frac{N_1^B}{N^B} \cdot \overline{E}_1^B + \ldots + \frac{N_i^B}{N^B} \cdot \overline{E}_i^B \tag{5.9}$$

Note that the relationship between the number of households in one group and the total number of households is the ratio of households in that group. Thus, this expression can be rewritten using these ratios:

$$\overline{E}^B = f_1^B \cdot \overline{E}_1^B + \ldots + f_i^B \cdot \overline{E}_i^B \tag{5.10}$$

$$\text{with} \quad f_j^B = \frac{N_j^B}{N^B} \tag{5.11}$$

This is an especially useful way to express $\overline{E}^B$ because it only depends on (1) an in-group average per household factor ($\overline{E}_j^B$), which, as shown in the next paragraph, are scenario invariant; and (2) the ratio of the groups in the scenario (f_j^B), which can easily be derived from the characteristics of any scenario.

A projection only varies a given variable while the others are kept constant (*e.g.* it varies the ratio of each type of building in the scenario). At the same time, the "value" of that variable is constant within each group (*e.g.* the "values" of the variable 'Type of building' are 'Apartments', 'Detached houses', etc. and they are grouped together). This means that group averages do not change when the group size varies following the characteristics of a scenario (*e.g.* in one scenario there may be more apartments, in another one more detached houses, but the average electricity demand of apartments and detached houses do not vary). Therefore, for a particular projection, the average electricity demand of each group can be considered scenario invariant. And this holds true for the rest of in-group average per household factors such as the average household size.

In the case of the previous equation, therefore, $\overline{E}_j^B = \overline{E}_j^{Sc}$ for each group j. In addition, the values of $\overline{E}_j^B$ can be easily found from the data. Then, once the average electricity demands of each group are found and the ratios defined for a scenario Sc, the average electricity demand per household in the scenario is given by the following expression where all the factors are known:

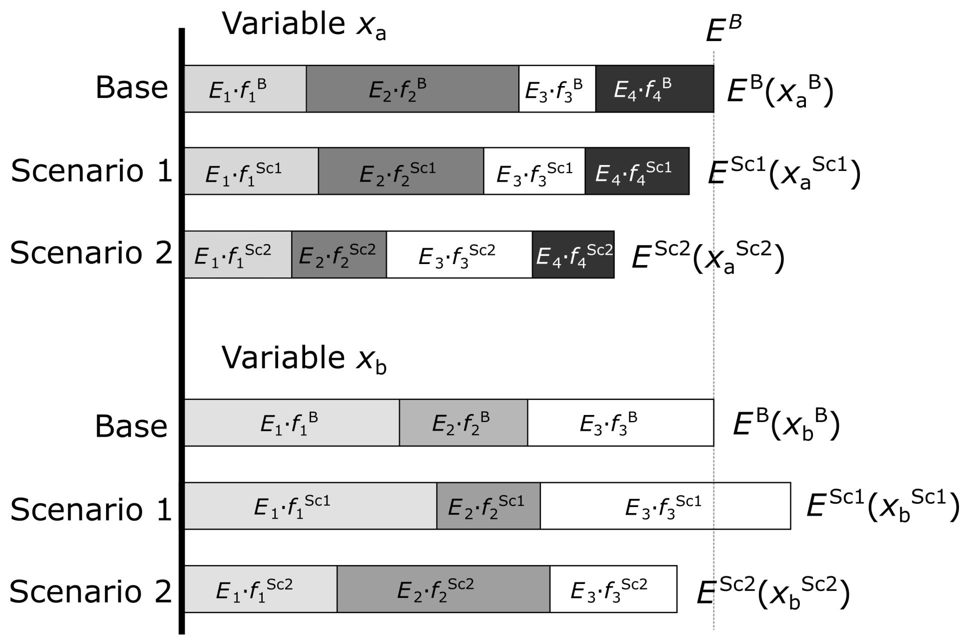
$$\overline{E}^{Sc} = f_1^{Sc} \cdot \overline{E}_1^B + \ldots + f_i^{Sc} \cdot \overline{E}_i^B \tag{5.12}$$

This way, with a simple ratio-weighted sum it is possible to obtain the projection of the average electricity demand per household in each of the scenarios for any variable. Note that these average electricity demands correspond to any given period of time, giving a huge flexibility to these projections.

Now that the expression is derived, its notation can be simplified. First, scenario invariant variables do not need to show information of the scenario to which they belong. And, as it is a given that the method deals with the average household electricity demand, to simplify the notation the top bar can be waived. The simplified expression is as follows:

$$E^{Sc} = E_1 \cdot f_1^{Sc} + \ldots + E_i \cdot f_i^{Sc} \tag{5.13}$$

A graphical comparison of the projections for two variables, x_a and x_b, in two scenarios plus the base scenario is shown in Figure 5.4.0.1. It shows that the average electricity demand in the base scenario is the same regardless of the variable chosen to express it, and how it may vary in different scenarios.



The average electricity demand in the base scenario is the same regardless of the variable chosen to express it, and that of the different scenarios depends on the variable projected.
For clarity, the projected variable is not shown by the factors.
Note that $E_j^B(x_a^B) = E_j^{Sc1}(x_a^{Sc1}) = E_j^{Sc2}(x_a^{Sc2})$ and the same for the variable b; and that in general $E_j(x_a) \neq E_j(x_b)$ and $f_j^{Sc}(x_a^{Sc}) \neq f_j^{Sc}(x_b^{Sc})$ as the groups are totally distinct (variable a could group by type of building and variable b by household size).

Figure 5.4.0.1: Example of a comparison of the total average household electricity demand in the base scenario and the projections to two scenarios for two different variables.

Typically, the narratives of the indicators convey their evolution relative to the base scenario instead of an absolute value, *e.g.* "XX% increase in detached houses" rather than "YY% of the stock are detached houses". If this happens, f_j^{Sc} can be easily found by applying these evolutions to the group ratios in the data. When the characteristics of the indicators convey absolute values but the group ratios in the data (f^{data}) are the same

—or very similar— to those in the base scenario, $f^B \approx f^{data}$, the scenario ratios can also be easily found. However, this is not the case when the indicators convey absolute values and the ratios are not similar, $f^B \not\approx f^{data}$. In that case the ratios derived from the scenario characteristics have to be transformed to change their origin, *i.e.* their origin must be the group ratios in the data set instead of the ratios in base scenario. This can be achieved by finding the relationship (λ) between the group ratios derived from the scenario characteristics with origin in the base scenario, $f^{Sc}_{B,j}$, and those in the base scenario (f^B_j), and applying the same relationship to the ratios in the data set (f^{data}_j):

$$\begin{gathered} f^B_j \cdot \lambda_j = f^{Sc}_{B,j} \Rightarrow \lambda = \frac{f^{Sc}_{B,j}}{f^B_j} \\ f^{data}_j \cdot \lambda_j = \nu^{Sc}_{data,j} \end{gathered} \tag{5.14}$$

However, although these ν_j convey the evolution followed by the scenarios, their sum will in general not be equal to 1, *i.e.* they are not ratios (from the definition of ratio in Expression 5.11, $\sum f_j = \sum N_j/N$; if $\sum f_j \neq 1 \Rightarrow \sum N_j \neq N$). Therefore, these ν_j have to be normalised to transform them into ratios, which is what the method requires. The normalisation is trivial:

$$f^{Sc}_j = \frac{\nu^{Sc}_j}{\sum \nu^{Sc}} \tag{5.15}$$

It is recommended to find the projection ratios this way also when calculations involving the metadata are needed in order to obtain the ratios in the base scenario or when the ratios in the base scenario are used to calculate corrections for the projection.

It is also useful to study the expression for the total electricity demand in the scenario. Looking back to Equation 5.9 (and redefining total electricity demand as E^{Sc}_T) its expression follows:

$$E^{Sc}_T = E^{Sc} \cdot N = N \cdot \left(E_1 \cdot f^{Sc}_1 + \ldots + E_i \cdot f^{Sc}_i\right) \tag{5.16}$$

The importance of this expression arises as it is usual that scenarios describe changes in their population which, in turn, affect the population of households. Changes in total population typically have to be considered by introducing a correction in Equation 5.16:

$$E^{Sc}_T = F^{Sc} \cdot E^{Sc} \cdot N = F^{Sc} \cdot N \cdot \left(E_1 \cdot f^{Sc}_1 + \ldots + E_i \cdot f^{Sc}_i\right) \tag{5.17}$$

Where F^{Sc} is the ratio in which the total household population has changed in the scenario. As scenarios normally inform about the changes in total population, one has to be careful to find the appropriate value for F^{Sc} which reflects the change in household population.

Both, group ratios (f_j^{Sc}) and population change ratio (F^{Sc}), do not change the amount of electricity demand per household of the groups but the relative or absolute amount of times that they are expressed, *i.e.* variations in the populations. However, some indicators may describe a change in the magnitude of the household electricity demand; sometimes homogeneously for the whole household population (Equation 5.18), sometimes different for each group of households (Equation 5.19). These changes in magnitude are easily introduced in the framework with corrections:

$$E^{Sc} = k^{Sc} \cdot E_0^{Sc} \tag{5.18}$$

$$E^{Sc} = k_1^{Sc} \cdot E_1 \cdot f_1^{Sc} + \ldots + k_i^{Sc} \cdot E_i \cdot f_i^{Sc} \tag{5.19}$$

Where k_j^{Sc} is the ratio that the average electricity demand of group j in scenario Sc varies with respect to that of the same group in the base scenario, k^{Sc} (note the lack of sub-index) is the ratio that the average electricity demand of scenario Sc varies with respect to the base scenario, and E_0^{Sc} is the average electricity demand of the scenario before applying the general correction (it is not relative to any group 0). Equation 5.18 is actually a particular case of Equation 5.19 used when a single class of households grouping all the household population together is adopted —normally by lack of detailed information— (then $E_0^{Sc} = E^B$), or when the correction is equal for all the population (then $E_0^{Sc} = E_1 \cdot f_1^{Sc} + \ldots + E_i \cdot f_i^{Sc}$). It is often the case that one needs to do calculations involving both, the group ratios in the future and base scenarios to find these corrections.

It is important to stress once more that, although the formalism for corrections and group ratios is equivalent, they represent very distinct phenomena which may carry consequences for the analysis of the projections. An example of this can be found in Section 5.6 below.

Projections with group ratios (f_j^{Sc}) and/or group corrections (k_j^{Sc}) cannot be applied sequentially to the results of another projection because the data are aggregated after being projected, therefore it is impossible to define new groups. However, projections which only consist of a general correction (k^{Sc}) can be applied to any E_0^{Sc}. Therefore, they can also be applied to the result of another projection and to this result sequentially. If the general correction accounting for the changes in the magnitude of the average electricity demand due to variations in variable m is $k_{x_m}^{Sc}$, then:

$$E^{Sc}(x_1^{Sc}, x_2^{Sc}, \ldots, x_n^{Sc}) = k_{x_1}^{Sc} \cdot k_{x_2}^{Sc} \cdot \ldots \cdot k_{x_n}^{Sc} \cdot E_0^{Sc} = K^{Sc} \cdot E_0^{Sc} \tag{5.20}$$

Where $x_1^{Sc}, \ldots, x_n^{Sc}$ are the variables which are made to vary to find E^{Sc}, and K^{Sc} is the multiplication of general corrections. Now, and not showing the projected variables for notation simplicity, an expression to obtain an aggregate of several general-correction-projections and a maximum of one groups-projection is the following:

$$E^{Sc} = K^{Sc} \cdot \left(k_1^{Sc} \cdot E_1 \cdot f_1^{Sc} + \ldots + k_i^{Sc} \cdot E_i \cdot f_i^{Sc} \right) \\ \text{with} \quad K^{Sc} = k_{x_1}^{Sc} \cdot k_{x_2}^{Sc} \cdot \ldots \cdot k_{x_n}^{Sc} \tag{5.21}$$

This expression, however, assumes all the general corrections contribute with the same weight to the aggregate, which may well not be the case: typically, different variables contribute with different degrees of importance to shaping a particular scenario. If this is the case, a weighting factor for each $k_{x_1}^{Sc}$ could be introduced.

It is important to note that scenario invariant factors introduce artefacts in other variables. For example, the average number of occupants per household in group j, n_j, is scenario invariant. One can easily calculate the total population of the scenario (total number of household's occupants), N_P^{Sc}, by adding up the total number of people in each group, $N_{P,j}^{Sc}$ (average number of occupants per household in group j, n_j, times number of households in the group, N_j^{Sc}), and substituting Expression 5.11 for group ratios:

$$N_P^{Sc} = \sum_{j=1}^{i} N_{P,j}^{Sc} = \sum_{j=1}^{i} n_j \cdot N_j^{Sc} = \sum_{j=1}^{i} n_j \cdot f_j^{Sc} \cdot N = N \cdot \left(n_1 \cdot f_1^{Sc} + \ldots + n_i \cdot f_i^{Sc} \right) \tag{5.22}$$

N_P^{Sc} can clearly be different for each scenario as N (total number of households) is constant, n_j (average number of occupants per household group) is scenario invariant and f_j^{Sc} change following the characteristics of each scenario. However, these variations are different for different projections and independent from the changes in population (or other variables) introduced by the characteristics of the scenario. Therefore, these variations have to be ignored when projecting the given variable. Still, expressions such as Equation 5.22 can be useful.

One may be interested in obtaining expressions for functions not directly dependant on in-group average per household variables (or, in general, in-group average per agent variables). In the cases when the metadata contain information of the relation between such functions, it will be possible to obtain the expression sought. For example, the projection of the average electricity demand per person (E_P^{Sc}) may be more informative than, or a good complement to, that of the average electricity demand per household. As the total number of house occupants (N_P^{Sc}) has been found in Equation 5.22, one can easily find the expression for such projection:

$$E_P^{Sc} = \frac{E_T^{Sc}}{N_P^{Sc}} = \frac{N \cdot E^{Sc}}{N \cdot \left(n_1 \cdot f_1^{Sc} + \ldots + n_i \cdot f_i^{Sc} \right)} = \frac{E^{Sc}}{n_1 \cdot f_1^{Sc} + \ldots + n_i \cdot f_i^{Sc}} \tag{5.23}$$

In a similar way, other expressions for projections of interest may be found if the metadata conveys enough information.

In summary, the method derived above consists of a ratio-weighted sum which is complemented with simple corrections. In its development, three conditions have arisen that the disaggregated data and the scenarios have to meet so that projections can be completed: (1) the set of disaggregated data contains sufficient metadata about the agent variables on which its behaviour depends (this only applies to the projections involving groupings), (2) these variables are characterised in the scenarios, and (3) the scenarios are not too disruptive. And expressions for projections with an agent which is not the same as the agent which produced the data can be derived if enough information is available.

5.4.1 Generalisation

This mathematical framework has been developed to project household electricity demand data into future scenarios. However, neither these data nor future scenarios have any intrinsic characteristic distinct than other kinds of disaggregated data and scenarios which is needed for the methodology to function. Therefore, the method is easily generalizable to project any set of disaggregated data (produced by any type of agent) to any scenario as long as they meet the conditions mentioned above.

The expressions which can be generalised, are those whose agent is the same as the agent which produced the data set. This, for example, is not the case of Equation 5.23 for the electricity demand per person, where the agents are persons/occupants instead of households. Such expressions have to be derived from the core framework in each case; however, as in the case above, this should not be difficult if the relevant information is known.

In order to generalise the equations, consider a general set of disaggregated data. These data present the values of '$\mathit{\Phi}$' produced by agents a, and includes metadata with information about the variables which influence the behaviour of a. The projection of these data into scenario Sc for the variable x_n, *i.e.* the average '$\mathit{\Phi}$' per agent across the whole agent population in the scenario, is $\mathit{\Phi}_a^{Sc}(x_n^{Sc})$:

$$\mathit{\Phi}_a^{Sc}(x_n^{Sc}) = \mathit{\Phi}_1 \cdot f_1^{Sc} + \ldots + \mathit{\Phi}_i \cdot f_i^{Sc} \tag{5.24}$$

Where $\mathit{\Phi}_j$ are the average '$\mathit{\Phi}$' per agent of each group, f_j^{Sc} the ratios of each group in scenario Sc, and the groups sort agents with the same (or similar) "values" of the variable x_n. If, on top (or instead) of the changes in the group ratios, the projection involves a change in the magnitude of these $\mathit{\Phi}_j$, some corrections must be introduced:

$$\mathit{\Phi}_a^{Sc}(x_n^{Sc}) = k^{Sc} \cdot \left(k_1^{Sc} \cdot \mathit{\Phi}_1 \cdot f_1^{Sc} + \ldots + k_i^{Sc} \cdot \mathit{\Phi}_i \cdot f_i^{Sc}\right) \tag{5.25}$$

Where k^{Sc} is a general correction affecting the whole population of agents and k_j^{Sc} are corrections to the magnitude of each Φ_j. Finally, we can find an expression for the total 'Φ' in the scenario:

$$\Phi_{Ta}^{Sc}(x_n^{Sc}) = F^{Sc} \cdot N \cdot k^{Sc} \cdot \left(k_1^{Sc} \cdot \Phi_1 \cdot f_1^{Sc} + \ldots + k_i^{Sc} \cdot \Phi_i \cdot f_i^{Sc}\right) \tag{5.26}$$

Where F^{Sc} is the ratio in which the total agent population changes in scenario Sc and N the total number of agents.

5.5 How to apply it?

This section explains how to use the mathematical framework developed above. This explanation is complemented with a flowchart, Figure 5.5.0.1, and an example, subsequent section, to facilitate its understanding. In order to be able to use the mathematical framework one needs disaggregated data and scenarios fulfilling the conditions previously stated.

The first step is to precisely define the variable or variables of interest. Then one needs to analyse the data and metadata to propose a draft of the groupings. The availability or lack of metadata and their details will influence the choice of groupings or even the definition of the variable(s). Next, one has to find the relevant indicator(s) and other information related to each variable in the scenario literature. If these are not directly compatible with the metadata, one can use external information to transform the metadata and propose the final groupings. If this is not possible, sometimes a proxy can be found in the metadata which can be used instead (*e.g.* use number of bedrooms as proxy for dwelling size). In case of total incompatibility or no information in the metadata, one could still estimate a general correction, k^{Sc}, following the characteristics of the scenarios and any relevant literature. This is then, however, not a real projection but a general correction of the data; *i.e.* if the metadata contained information about the variable, the projection may have needed a ratio-weighted sum. This same procedure is used when the scenario narratives show that the effect the variable has in the scenarios is to change the magnitude of the data values homogeneously. In this case the general correction corresponds to the projection of the data.

When the information from the scenarios and that in the metadata are compatible, and the scenarios indicate that the characteristics of distinct groups of agents are different, the ratio-weighted sum will be used. To do that, one needs to find the ratios of the groups in the base scenario, in the data set, and derive the ratios in the scenarios following their characteristics. The process of finding the group ratios in the scenarios may be more or less straightforward. It depends on whether or not external literature is needed, the ratios in the base scenario and in the data are similar, and on the scenario characteristics. Finally, one can use these ratios, f_j^{Sc}, to do the projection. In some cases, when the characteristics of the scenarios indicate it, a correction has to be found for each group, k_j^{Sc}, to do the projection. Other times, when group ratios do not change but the magnitude of electricity demand does, only these corrections are needed.

Finally, when the variable conveys information of a change in the total population of agents, F^{Sc} has to be found and applied to the relevant equation.

Figure 5.5.0.1 is a flowchart portraying this method. Light grey nodes indicate a correction which affects the magnitude of the data values, and dark grey indicate a change in the total number of agents or in the size of the groups of agents. Dashed lines indicates the branches of the flowchart that are estimations, not projections based on the method developed in this chapter.

5.6 Projection example

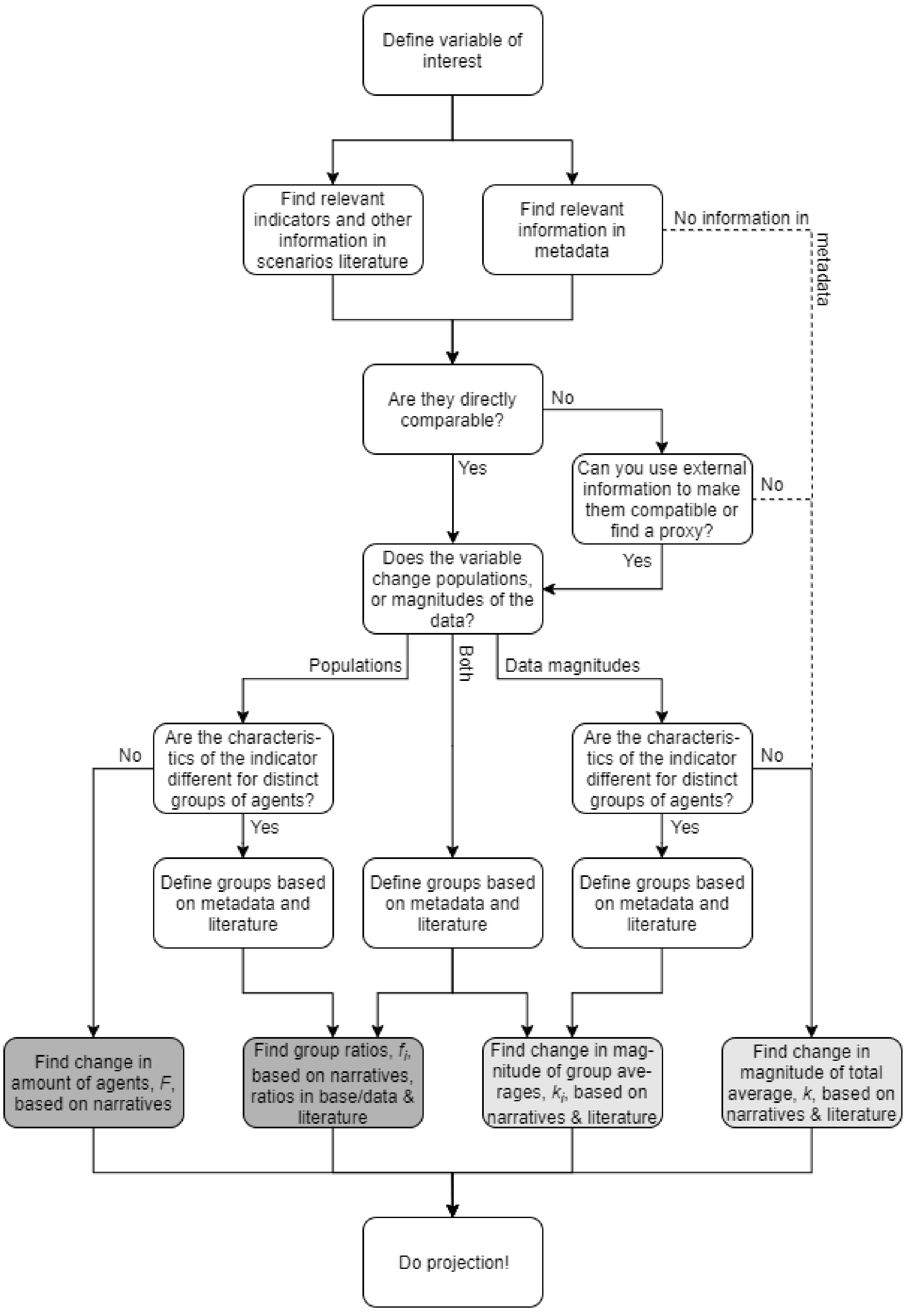
Although next chapter is devoted mainly to using the tool developed above to project real data, it may be helpful to first see a simple hypothetical example to illustrate the use of this framework. The values included in the following example are only for illustrative purposes as what is relevant here are their relative changes. The groups in which the data are sorted have very distinct daily electricity demand profiles to highlight the differences between projections.

The total average household electricity demand per day in the sample is 0.9265 kWh and the total average electricity demand profile per day is shown in Figure 5.6.0.1 a) (in kWh as well).

Following the properties of the variable (found in the metadata), the data are sorted into 3 groups, which are named 'Morningers', 'Eveningers' and 'Constanters'. These groups exist in the same proportion in the sample, *i.e.* their ratios are 0.33. The average electricity demand per day of each group are, respectively, 0.8579, 0.8937 and 1.0561 kWh, and their average electricity profiles (in kWh) are shown in Figure 5.6.0.1 c).

The ratios and corrections are obtained following the characteristics of the variable in the different scenarios, see Table 5.6.0.1. In scenario 1 (Sc1) the magnitude of the electricity demand of the groups does not vary with respect to that in the data, and in scenario 2 (Sc2) it varies for all groups with differing degrees. In scenario 3 (Sc3), the relative electricity demand between groups is maintained almost constant, only that of Eveningers increases slightly, but the global electricity demand decreases substantially.

The average electricity demand per day of Sc1 is 0.9119 kWh, that of Sc2 is 0.9478 kWh, and that of Sc3 is 0.6911 kWh, and their average electricity profiles (in kWh) are shown in Figure 5.6.0.1 b). A comparison between the profile of group Eveningers in scenario 1 and 2 is shown in Figure 5.6.0.1 d) to portray the difference in the magnitude of their electricity demands.



Light grey indicates corrections which affect the magnitude of the data values, and dark grey indicates corrections or ratios which affects the total agent population or the size of the agent's group. Dashed line indicates estimation, not actual projection.

Figure 5.5.0.1: Flowchart of the method to apply the mathematical framework.

Table 5.6.0.1: Corrections (general and for each group) and ratios obtained for each group in each scenario.

Scenario	k	Morningers		Eveningers		Constanters	
		k_M	f_M	k_E	f_E	k_C	f_C
Sc1	1.0	1.0	0.4	1.0	0.4	1.0	0.2
Sc2	1.0	1.1	0.4	1.3	0.2	0.8	0.4
Sc3	0.7	1.0	0.2	1.1	0.4	1	0.4

This is a hypothetical example which exaggerates the differences between scenarios by making the data of the different groups very distinct to help to visualise the effects of the projection. In general, an analysis of the projections obtained would provide information of the likely behaviour of the household electricity demand in each scenario, and their differences and particularities. One could then test the resilience of any intervention that could be taken today against these effects, or complement other futures analyses in that domain.

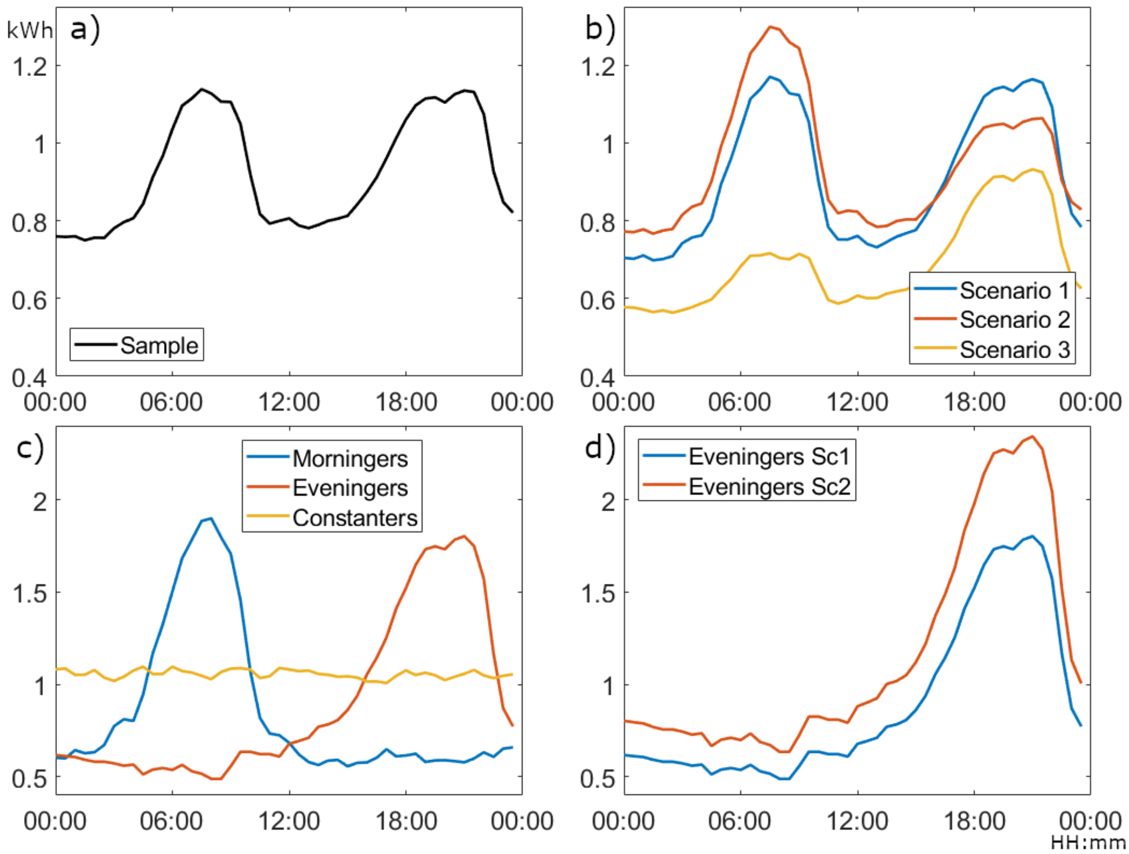


Figure 5.6.0.1: Daily average electricity demand profiles in kWh of: a) data sample, b) future scenarios, c) groups of households (Morningers, Eveningers and Constanters), and d) group Eveningers in scenarios 1 and 2 —it shows the change in magnitude introduced by the different values of k.

Analysis of outcomes

Although this is just an example, the outcomes obtained can also be briefly analysed to illustrate possible measures that could follow. One can see that the electricity demands in the different scenarios are quite variable, especially the peaks. Therefore, it might be advisable to prepare the electricity network to be flexible so that it can be rapidly adjusted to any of the scenarios without wasting a lot of resources to cope with the highest possible peak. At the same time, scenario 1 and scenario 2 have a similar daily electricity demands to that in the base scenario while their peaks are taller (larger peak-to-average ratio), and in scenario 3 only the morning peak is lower than the off-peak demand in base scenario; therefore, the addition of energy storage to help smooth the electricity production would be beneficial in all scenarios.

Also, depending on the priorities of regulators or the possibilities of the electricity network, some group could be incentivised over the others, for example, by means of tariffs directed to each group. As large peaks are usually a problem for the network, Eveningers and Morningers could be offered a cheaper price outside the time of their peak demand to incentivise them to spread their demand of electricity through the day. Another possibility for regulators would be to investigate the root cause for the distinct behaviours of the scenarios and attempt to promote the most favourable scenario.

This is, of course, a very extreme and simplistic example. In reality the differences in electricity demand between different households groups are never going to be as distinct. Therefore, it is likely that the analysis will not be as clear-cut. However, such a simple analysis helps to clarify the possibilities this tool offers.

5.7 Discussion of the tool

The main use of the tool presented here is to compare the resulting projections with the original data, *i.e.* analyse the differences between the behaviour of the data and that of their projections in the future scenarios. Therefore, if the data are representative of any domain of the real world, one can assume that the conclusions obtained from analysing the projections can be broadly applicable to that domain, reducing its future uncertainty. Thus, one could test any intervention or design against the projections for each scenario to analyse its performance. If it performs well against the projections in all scenarios, the intervention is very likely to be resilient. If not, that analysis can serve as an aid to improve the intervention. These are rather detailed insights that may also be a valuable addition in the context of a broader futures analysis.

This method relies heavily on data and metadata of good quality, which may be difficult to obtain. However, when the data is poor or not representative of the normative environment from where they were taken, an analysis of their projections may still give useful information for a futures analysis.

Three conditions have emerged during the development of the framework that have to be fulfilled in order for projections to be possible: (1) the set of disaggregated data contains sufficient metadata about the agent variables on which its behaviour depends, (2) these variables are characterised in the scenarios, and (3) the scenarios are not too disruptive.

From these conditions, condition (1) applies only to projections for which groupings are needed, as general corrections can always be obtained. However, this is only a blind approximation when this is done because of the lack of information to define the groups. Regarding condition (3), the scenarios are too disruptive when they include behaviours or properties of the agents which do not exist in the base scenario or in the environment the data come from (*e.g.* specific new technologies, new or different groups of agents, step changes in agent behaviours, etc.). Obviously, when data are lacking for a group, it is impossible to project them. Similarly, when a group is not absent in the base scenario or data set but its population is very small, its projection into a scenario where its weight is greater may not portray a representative picture due to lack of statistical power.

If condition (2) is not fulfilled, the information on which to base the group ratios or the corrections is lacking from the scenarios. In these cases, however, scenarios may be expanded to include the information needed (Banchs-Piqué et al., 2020; Boyko et al., 2012). This is especially the case when scenarios already contain information closely related to the missing indicators. Therefore, although this framework cannot take into account anything which is not described in the scenarios, the scenarios can be modified or new scenarios created to include the desired information. In this same line of reasoning, this method has been designed to be applied to groups of scenarios developed together, with the same set of indicators and base scenario. However, when a coherent set of relevant indicators can be extracted or derived from differently built scenarios, this method could also be used to project data into them. Then, besides deriving the mentioned set of indicators, the group ratios found would have to take into account that each scenario evolves from different base scenarios.

Although the framework was developed with the primary intention to project disaggregated sustainability-related data into future scenarios, the temporal standpoint of the scenarios and the type of data do not have any intrinsic characteristic needed for the framework to work. This means that the framework can be useful to obtain information on how any set of disaggregated data could behave in alternative scenarios where the environment of the data would be different in some aspects. Therefore, a broad spectrum of disaggregated data could be projected into relevant scenarios (*e.g.* star brightness data into alternative universe scenarios, or consumer purchasing behaviour data into different market scenarios). This is especially relevant with the current explosion of data generation.

There are two types of variables, those the "values" of which are totally discrete or distinct (*e.g.* the "values" for the variable 'Type of building' are discrete: 'Detached house', 'Apartment', etc.), and those the values of which describe a progression or scale (*e.g.* more or less insulation for the variable 'Dwelling insulation'). To describe groups in the latter case, more or less arbitrary ranges have to be defined. These ranges will depend, to a large extend, on the information the metadata convey about the variable and on the distribution of the agent's values for the variable. However, a degree of subjective judgement is unavoidable.

In groupings of variables with progressing values, when most of the agents fall at one of the extreme groups and the other groups are much less populated —very skewed distribution—, it is not possible to use the ratio-weighted sums to project in the "direction" to that extreme. For example, if most of the households fall in the group of 'very well insulated dwellings' and very few in the lower insulated groups, it is not possible to use the ratio-weighted sum to project the data into a scenario where households are better insulated. This could be seen as the scenario being too disruptive. However, it is normally rather due to lack of information in the metadata to craft better groups.

The scenario invariant variables sometimes introduce changes in the value of other variables; these are different for different projections. These variations are artefacts independent of the characteristics of the scenarios and must not be taken into account when projecting these other variables. Also, problems arise when a change of origin has to be performed to obtain the group ratios in the future scenarios. For example, when the data were sorted in a number of groups and, for whatever reason, two or more groups are merged, all the resulting ratios vary. In these cases, it would be expected that all the ratios stay constant except for these of the merged groups, which would be summed.

The fact that the averages used in the framework are not associated with any length of time and can be obtained from any kind of disaggregated data, gives the projections a huge flexibility. Continuing with the example of household electricity demand, one can equally easily obtain the projection of the average daily demand profile or that of the average electricity demanded in one year. Additionally, the projection of the total household electricity demand and that of the electricity consumed by a particular appliance are also equally easy to obtain. It all depends on the information the data include.

Although the framework is simple in form and concept, its application may be less so. Besides the interconnectedness of the variables, which may make it impossible to define a set of independent variables which cater for the domain of study without gaps, it is often not straightforward to adapt the information in the metadata to that of the scenarios and to find how the variation in the characteristics of the scenarios affect the data. Therefore, relevant literature must often be carefully reviewed to perform these tasks accurately. Still, this is simpler, more specific and more direct than using complex computer modelling to project aggregated data.

Scenarios usually describe complex adaptive systems. Therefore, variations in the characteristics of the indicators could potentially have huge unintended consequences. Typically, these consequences are attempted to be taken into account in the process of scenario building. However, this is done in a macro-scale level and the consequences may be very different at the micro-scale level. Therefore, any projection using the method presented here has to be taken as a partial estimation, never as a conclusive result. Even if the endless interconnectivities and detailed consequences of such alterations where deeply studied and used to study the behaviour of some data in a future scenario, taking the results as conclusive would be adventurous. For this reason, it is recommended to project data by varying as many relevant variables in the domain of study as possible to have a broader insight of its behaviour in the scenarios.

These interconnectivities are, at the same time, the reason why combining projections of different variables in a single aggregate is a complex matter outside the scope of this thesis. A manual combination of different projections should be feasible if the relation between the variables projected and how they affect the behaviour of the data in the scenarios is known. For example, one could do a weighted sum of the different projections if one is able to propose reliable weights. However, a systematic method to do that is complex to design and would, without a doubt, be a very useful addition to this framework.

It is important to note that when a scenario is heavily shaped by one specific (group of) variable(s), the projections of other variables portray effects of very secondary order. Besides, two scenarios may be heavily shaped by distinct variables. Thus, not only the contributions of the various projections will be different when aggregating them for a given scenario; but also the projections of a given variable will have different contributions (weights) to the aggregate of each scenario. These are important factors to be taken in consideration when attempting to aggregate a set of projections to obtain a single meaningful picture of the scenario. For example, a scenario aggregate made up of very few but key projections may be more informative than an aggregate comprised of many projections which give information of secondary order.

Note that projections involving groups of agents cannot be applied to the results of another projection sequentially. This is because projections aggregate the data, thus eliminating all information of individual agents. Without this information, groups cannot be made. However, general corrections can be applied sequentially and, thus, be combined to form an aggregate. But then, again, one needs to take into account that projections for different variables may contribute with varying degrees to the aggregate of the scenario.

When using the framework to obtain projections in a domain of study rather than for a specific variable (*e.g.* the household electricity demand) it is important that the domain and the variables of interest are precisely defined. A plethora of variables with different levels of interconnectivities may be involved in the behaviour of the data in the domain. Therefore, it is typically difficult to find a set of independent variables which cater all these behaviours, and there will usually be some degree of overlapping and gaps between the variables. The set of variables chosen for the study will determine in some degree the outcomes of the projections. At the same time, it may easily be the case that either the metadata available do not contain information about some of the variables or that the scenarios have to be modified to include missing details. For all these reasons, the projections obtained are going to be meaningless without enough understanding on why they are needed, what information they convey, and what is their relation and place within the rest of projections. With a good understanding, however, these projections give details which may be very useful in a futures analysis.

A positive aspect of obtaining a set of projections to study a given domain is the fact that each projection shows the contribution of varying a single variable. Underlying dynamics that would not be apparent in a simulation can thus be easily detected.

5.8 Summary and conclusions

The futures studies lack a simple tool to project disaggregated data into future scenarios. Here such a tool is developed. The tool comprises a mathematical framework and the method to apply it. First, the tool to project disaggregated household electricity demand data has been developed, and subsequently it has been generalised to any set of disaggregated data. Its use has been shown with an example.

This method has a ratio-weighted sum of groups of agents in its core which, together with corrections, can simulate the behaviour of the data in the different scenarios one variable at a time. The evolution of these behaviours with respect to the original data reduce the future uncertainty decision-makers have to face by identifying and quantifying a range of plausible paths the data could take in the future.

This tool can be used with scenarios described by a set of indicators of which at least some are related to the data intended to be projected. The data must include enough relevant metadata related to these indicators and the scenarios cannot be too disruptive to be able to obtain a projection. However, none of the conditions mandate that the scenarios have to describe the future.

This process can be repeated for as many variables and scenarios as needed. The analysis of these projections can aid the design of any kind of intervention, plan or regulation to improve their resilience, which is especially relevant in the field of sustainability. They can also complement other futures analyses by giving deeper insight on a specific domain for which disaggregated data are available.

Although the tool is simple in form and concept, it may not be straightforward to use. Typically, the relevant literature has to be reviewed to adapt the metadata and/or the information about the scenarios, and to define the group ratios or the value of the corrections.

In order to study the behaviour of a specific domain in a range of scenarios, a number of projections varying relevant variables can be performed. The resulting batch of projections could be combined into an aggregate using information on how the different variables interact with one another and with the scenarios. However, a systematic method to combine such projections is outside the scope of this work.

Part III

Projecting household energy data into future scenarios

Chapter 6

Data projections

You never change things by fighting the existing reality. To change something, build a new model that makes the existing model obsolete.

— Buckminster Fuller

In this chapter, the tool developed above is used to project electricity and gas demand data into the DRC scenarios supplemented in Chapter 4. Before that, the chapter sets the basis for obtaining these projections (time periods, formats, etc.), explains the characteristics of the data and the trials where they were obtained, describes how the data was managed, and analyses the data that was projected. Then each variable is defined; and for each of them, the factors are derived and the projections obtained. The projections are then briefly analysed and, to conclude, a summary with a general analysis and conclusions are presented.

6.1 Before projecting

Before attempting to project any data, some aspects of the projections have to be defined: the time periods for which to obtain projections, the format of the projections, some particularities of the FW (Fortress World) scenario and the variables which can or cannot be projected.

Household energy demand, especially that used for heating, is very much influenced by the outside temperature (Fazeli et al., 2016). Therefore, it is important to obtain projections for periods of days with distinct temperatures ranges. The periods chosen to produce projections have been the different seasons and the whole year. Besides these periods, it is also valuable to investigate the hottest and coldest days of the year. Another temporal variable which affects the energy demand of households is the day of the week, with a major distinction between week-days and weekend-days (Richardson et al., 2008). Accordingly, the projections of the different periods are obtained for 'All Days' (AD), 'Week-Days' (WD) and 'WeekEnd-days' (WE).

Two sets of household energy demand data are projected, one is electricity demand data and the other one gas demand data, and both belong to Irish households. From now on these sets of data are referred to as Edata (electricity demand data) and Gdata (gas demand data). Both sets contain metadata (taken in telephone surveys) about different aspects of the households the data belong to, these surveys provide the metadata needed to obtain the projections. Edata starts on 14 July 2009 and ends in 31 December 2010, and Gdata starts on 1 December 2009 and ends on 30 May 2011. These data sets and the trials where they were obtained are explained in more depth in the next section, Section 6.2.1.

The Northern Meteorological Seasons definition has been chosen to define which days belong to which season. With this definition, each season begins on the first day of the month that includes the equinoxes and solstices (Trenberth, 1983) (therefore, the astronomical seasons begin 21 or 22 days after these seasons). As the two sets of data overlap for longer than one year and the overlap includes all meteorological seasons, the periods chosen to project the data are these which overlap, see Table 6.1.0.1. However, the meteorological season immediately before and after that period were monitored in Edata and Gdata respectively. These seasons can be used as a comparison for the household energy demand in the samples and for the projections.

The Irish historic weather data do not contain data about the hottest and coldest days of the year. Different weather stations provide, however, data about the hottest and coldest air temperature recorded for each day. The WD and WE with the hottest temperature recorded in summer 2010, and the WD and WE with the coldest temperature recorded in winter 2009-10 in Gurteen station have been chosen as hottest and coldest week-/weekend-days. Gurteen weather station is located in the county of Tipperary (very much in the centre of Ireland) and has a long enough history of the readings needed. This weather station was chosen because Edata and Gdata were taken from households spread all around Ireland without any reference to their specific location and the weather data from weather stations across the geographic areas of Ireland show reasonably consistent conditions (Kavousian et al., 2015). Therefore, a location in the centre of Ireland is, in aggregate, the closest point to these households. In order to access the historical data of Gurteen, from where its daily hottest and coldest air temperature recorded can be obtained, one needs to access the Historical weather data from Irish stations (The Irish Meteorological Service, n.d.), select the county of Tipperary, and there find Gurteen weather station.

A brief analysis of the monthly average temperatures of this weather station in the period 2009-2019 shows that the average amount of months where the temperature is outside the range 'average temperature of the month ± standard deviation' is 7.5 per

Table 6.1.0.1: Start and end dates of the data sets and of the different seasons (including hottest and coldest days, and comparing seasons) for which projections have been obtained.

	Starting day	Ending day
Edata	14 July 2009	31 December 2010
Gdata	1 December 2009	30 May 2011
Year	1 December 2009	30 November 2010
Winter	1 December 2009	28 February 2010
Spring	1 March	31 May 2010
Summer	1 June 2010	31 August 2010
Autumn	1 September 2010	30 November 2010
Hottest day	WD: 21 June 2010	WE: 20 June 2010
Coldest day	WD: 8 January 2010	WE: 9 January 2010
Compare Edata (Autumn)	1 September 2009	30 November 2009
Compare Gdata (Winter)	1 December 2010	28 February 2011

year, with a standard deviation of 2.4. In the twelve months chosen to obtain annual energy demand values, this number is 7, which is well within the normal range. Therefore, the year for which the projections are performed is not an outlier as a whole. Analysing season by season, the winter is particularly cold, with all the months having a temperature lower than the monthly average in the period minus the standard deviation (this is also the case for the next winter, the *comparing season* for Gdata). All the months of spring fall within their normal range of temperatures (this is also the case for autumn 2009, the *comparing season* for Edata). And for both, Summer and Autumn, their two first months fall within their normal range of temperatures while the last month is, on average, colder. A table with the average monthly temperatures in Gurteen's weather station for the period 2009-2019, the average temperature of the whole year, the standard deviation of each month and the number of 'off-months' per year can be found in Appendix C.2.1.

The projections are presented in two formats for each period of time and type of day: the daily average energy demand and the average daily profile. Daily profiles are obtained by averaging the energy demand of each of the 48 periods of 30 minutes in the day, and the daily averages by adding them up. These projections show the energy demand per household; however, the different characteristics of the variables projected to the future scenarios lead to different average numbers of occupants per dwelling. The average energy demands per person are also calculated for all the periods and type of day, and in the daily average and daily profile formats. From now on the capitalised word *EVERYTHING* is used to refer to all these formats, periods of time, types of day, per household and person.

The data are projected to the four scenarios described in Table 4.1.0.1 in Page 38, which are characterised by the extended DRC. FW is a special case of a scenario where the population is divided between two blocks, the rich (the haves) and the poor (the haves-not). These two blocks are systematically characterised differently. Therefore, the easiest way to distinguish them is to obtain one projection for each block and add them together (taking into account their weights) to obtain the projection for the whole FW scenario. The relation between FWr (FW rich) and FWp (FW poor) characterised in DRC is 35:65, which are the ratios of rich and poor households in FW. This ratio has its origin in the base scenario. Therefore, this relation is different and distinct when taking as origin Edata and Gdata (see Expressions 5.14 in Page 77). Following the definition and ratio of each social class (find them in Section 6.5.6), the rich are considered to be those households in social classes A and B, while the rest of the households belong to the poor. The resulting ratios of these blocks for Edata and Gdata, which correspond to the weights for the projections for FWr (W_{FWr}) and FWp (W_{FWp}), can be seen in Table 6.1.0.2. Their development can be found in Section 6.5.6, where the factors to project 'Energy purchasing power' are worked out.

Table 6.1.0.2: Weights of the projections for FWr and FWp to obtain FW.

	Edata	Gdata
W_{FWr}	0.13	0.28
W_{FWp}	0.87	0.72

There is another characteristic of FW which, in principle, complicates obtaining projections for this scenario: almost half of the population in FWp live in informal settlements (see the development of the variable 'Type of building', Section 6.5.8). The energy demand dynamics in informal settlements are varied; in most cases these exist without the usual residential infrastructure, including no gas or electricity infrastructure. However, a diverse percentage of the households in these settlements can sometimes be legally or illegally connected to the electric grid (Kovacic et al., 2016; Makonese et al., 2016; Soares Gonçalves et al., 2014; Tshabeni & Freere, 2017). Illegal connections usually can only be used for lighting and other low-power services as they usually lack enough voltage to power electric appliances (Kovacic et al., 2016; Lloyd, 2014). However, on other occasions, the electricity demand of these settlements can be comparable to that of formal settlements (Soares Gonçalves et al., 2014). Something similar happens with gas demand, with cases ranging from almost no, or very sporadic, use (Lloyd, 2014; Makonese et al., 2016) to cases where the use is comparable to that in formal settlements (Butera et al., 2016).

Due to this range of possible behaviours, and using the precautionary principle, the projections for FWp assume the energy demand of those in informal settlements is similar to that of those in formal settlements. This means that no differentiation is made within FWp between those living in formal and informal settlements when performing the projections. Therefore, these projections have to be considered as an upper limit or worst case scenario, which is what is anyway demanded for planning purposes.

The variables for which projections are obtained are found in Table 6.1.0.3. This table also shows whether the projection for the given variable entails variations in group ratios and/or corrections, the grouping criteria (when groups are defined), and for which data set they are performed. There have been two variables for which projections could not be performed. These variables are 'Time spent at home' and 'Microgeneration'. The reasons why they could not be projected are subsequently explained.

Table 6.1.0.3: All projected variables (plus groupings, type of projection and data).

Variable	Data groupings	Ratio-weighted sum	Correction(s)	Edata	Gdata
Number of households	–	×	✓'	✓	✓
Attitudes to energy efficiency and sustainability	–	×	✓	✓	✓
Energy efficiency of appliances	–	×	✓	✓	×
Energy efficiency of dwellings	– (+)	×	✓	×	✓
Percentage of children in the household	Percentage of <15 in household: 0%, $(0, 50)$%, 50%, $(50, 100]$%	✓	×	✓	✓
Energy purchasing power	Social class: AB, C1, C2F, D, E	✓	✓	✓	✓
Space heating(*)	Only electric heating, gas and non-electric heating	✓	✓	✓	✓
Type of building	Flat, semi-detached, detached, terraced	✓	×	✓	✓
Number of bedrooms	Number of bedrooms: 1, 2, 3, 4, 5+	✓	✓	✓	✓
Appliances ownership and use	Appliance points: $(-\infty, 10]$, $(10, 20]$, $(20, 30]$, $(30, 40]$, $(40, \infty)$	✓	×	✓	×
Energy poverty	Energy poor, not energy poor	✓	×	✓	✓
Household size	Household members: 1, 2, 3, 4, 5, 6+	✓	×	✓	✓

The table shows whether (✓) or not (×) each variable entail a ratio-weighted sum or corrections, and if they are applied to Edata or Gdata. When ratio-weighted sums are used, it also shows the grouping criteria. ✓': in 'Number of households' the projection is a change in the population of households (not a correction of their energy demand). (+): Groups were set for 'Energy efficiency of dwellings' but it was not possible to use them to obtain projections, therefore they are not shown. (*): 'Space heating' is projected with a ratio-weighted sum for Edata, with the groups shown here, and for Gdata it is a change of total population of households using gas.

Time spent at home: there is one indicator which is to some extent related to it in DRC; it is called 'Work time'. However, it only accounts for working people. In addition, it is not clear how to relate it with the time people spend at home (people are not necessarily at home when they are not working and their behaviour would be different in different scenarios) and with the information conveyed by the metadata. The metadata contains information about how many people generally stay at home during the day for each household; this amount includes employed and (mostly) unemployed people, and there is no further information about the length of time these occupants are at home.

Microgeneration: the metadata do not contain information about households using microgeneration. The questions about space and water heating include the possibility to answer 'renewable' as the system. However, almost no household chose this answer. The reason is probably because the data are from the period 2009-2011 and from Irish households. Microgeneration was at the time much less common than now, especially in a country with few hours of sun as Ireland (see, for example, the global wind and solar installations in the period 2000-2018 by BloombergNEF in (Hodges, 2018)).

6.2 Origin of the data

The household energy demand data that are projected were obtained in the CER (Commission for Energy Regulation, now Commission for Regulation of Utilities (CRU) (CRU, n.d.-a)) smart metering project and were accessed via the ISSDA (Irish Social Science Data Archive (Irish Social Science Data Archive, n.d.)). These data are anonymised. The purpose of this project was to undertake trials to assess the performance of Smart Meters, their impact on consumers' energy demand and to evaluate the economics of a national rollout. There were two trials, one for electricity and one for gas, each of which obtained a dataset (Commission for Energy Regulation [CER], 2012a, 2012b). Both trials started with a benchmark period followed by a period where different stimuli and tariffs where applied to distinct groups of households. Those periods were roughly six months and one year long respectively. The repository with all the documents related to this project can be found in (CRU, n.d.-b).

6.2.1 Data collection trials

The Smart Metering Electricity Customer Behaviour Trials took place during 2009 and 2010 with over 5,000 Irish homes and businesses participating, and the Smart Metering Gas Customer Behaviour Trials during 2010 and 2011 with nearly 2,000 Irish homes participating. Those trials were independent and, as the data were anonymised, there is no information on whether there are any participants which took part in both. The participants in the trials had an electricity or gas smart meter installed in their homes and agreed to take part in the research to help establish how smart metering can help shape energy usage behaviours across a variety of demographics, lifestyles and home sizes. Both trials performed a pre- and post-trial survey in which different aspects of the household's demographics, dwelling and energy related opinions were asked. The pre-trial surveys have been used as source of the metadata needed to obtain the projections.

Both trials ensured the outcomes to be robust and representative of the Irish population by phasing their recruitment process. After each phase the representativeness of respondents who opted in was analysed. Once the recruitment was completed, the consumers who had not accepted were compared with those who had in order to confirm the representativeness of the latter. The dimensions included in these analyses were overall usage and location as well as a combination of other factors (CER, 2011b, 2011c). Before the trials, the researchers who performed them, did not have any information on demographics, household profile or indications of factors such as discretionary use of energy (CER, 2011a).

In order to minimise attrition, the studies excluded short term tenancies. This reduced the proportion of apartments and small houses (terraced) in the samples, as well as of younger age profiles and participants who live alone. Fuel poor consumers are also under represented in the sample. Households with NightSaver tariffs were excluded from the trial, this relates to the under representation of households with electrical heating in Edata. In terms of gender, there is a higher proportion of non-responding females (without any immediate explanation), and in terms of attitudes towards energy reduction the non-respondents tended to be less engaged with energy reduction and less likely to believe that they can affect what they consume (which fits the self-selection nature of the recruitment process) (CER, 2011a, 2011b, 2011c).

The results of the electricity trial concluded that the deployment of time of use tariffs and stimuli for demand side management reduced the overall electricity consumption by 2.5% and the peak usage by 8.8%. The reductions tended to be larger in households with higher consumption. The detected benefits of the trial were focussed on the behaviour changes in response to the tariffs and stimuli, and no secondary benefits were identified (increased awareness of general energy efficiency or increased investment in energy efficiency enhancements for the home). The main conclusion of the gas trial was that the deployment of stimuli reduced the overall gas consumption by a statistically significant 2.9%. And that 70% of this reduction was during high usage period (Oct-Mar) and 30% during low usage period (Apr-Sep) (CER, 2011a, 2011b, 2011c).

These reductions in the energy that households demanded during the period of the trials do not affect the analysis of the projections performed with these data. The projected data is the benchmark in which to compare the projections to analyse the changes in their behaviour conveyed by the scenarios. These changes in behaviour are not absolute but in relation to this benchmark. Therefore, the fact that the behaviour of the agents which produced the data changed within the projected periods does not affect the analysis of the projections.

6.2.2 Characteristics of the data

The electricity consumption data come in 6 .txt files of around 100 MB each. These contain the electricity readings for 4225 dwellings, 485 SMEs, and 1735 "other" (participants who did not complete the trial because they attrited, were excluded for technical reasons, etc.). The gas consumption data come in 77 files (without extension) of roughly 10 MB each. They contain the gas readings for 1493 dwellings. All data files are composed of 3 columns. The first one corresponds to the ID of the meter. The second one contains a five-digit code of the date and time of the reading: digits 1-3 code the day (day 1 being 1st January 2009), and digits 4-5 code the time of the day (1-48 for each 30 minutes of the day, with 1

= 00:00:00 – 00:29:59). The third column corresponds to the average power consumption in the corresponding 30-minute interval in kW.

The description in the manifesto file for Edata is wrong. It states that the values in the third column corresponded to the electricity consumed during the 30-minute interval expressed in kWh (*i.e.* energy) instead of in kW (power). Values obtained following this wrong premise would be off by a factor of 2 (energy is equal to power multiplied by time; as the periods are of 1/2 of an hour, to obtain the energy in kWh consumed in half an hour, one has to multiply the power in kW by 1/2, *i.e.* divide it by 2). The manifesto file for Gdata is correct.

There are some data missing in the samples. In Edata, these missing data are always in multiples of 48 data points (full day of readings). The amount of missing data-days is 635 out of a total of 2260375 (4225 dwellings times 535 days) theoretical data-days, which is a 0.024%. The maximum amount of data-days missing for a particular ID is 3 out of 535 days of monitoring, which is a 0.561%. Therefore, the level of uncertainty introduced by missing data is very low. In Gdata, six days do not have data at all (days number 616, 630, 631, 632, 869 and 870), and two other data-points are missing. This is 1.1% of the data-points[1], which also introduces very low uncertainty.

Some of the time periods projected contain GMT day light saving changes. These are reflected in Edata but not in Gdata, where all days contain 48 data-points[2]. For Edata, GMT day light saving changes affect the daily energy demand profiles, which are obtained averaging the data of each half an hour period of the day, but do not affect the total average daily energy demands (one day contains one hour of extra energy demand, while another day misses one hour of energy demand[3]). In the cases where one day is 25h long, the two extra readings of that day (reading number 49 and 50) have been ignored. In the cases where one day is 23h long, the average energy demand of readings 47 and 48 is obtained with the data of all the days except the shorter one.

Both samples come with metadata obtained with a pre- and a post-trial survey. This information comes, for both trials, in 5 files: 2 .doc files containing the CATI coded surveys (questions, possible answers, and guides for the surveyors), one for the pre-trial and one for the post-trial surveys; 2 data files containing the answers of the participants (one for each survey); and an allocation file linking the IDs with information about tariffs and stimuli and, for Edata, also with the information about whether they are SME, residential or other. The files containing the answers of the surveys are formatted as follows: the first row contains a summary of the question and its number, and the subsequent rows correspond each to one respondent, with the first column showing the ID of the respondents. The pre-trial surveys were used as metadata to obtain the projections. A copy of the CATI coded

[1] 429986 data-points missing (6 days times 1493 dwellings times 48 data-points per day) out of 39056880 data-points (545 days times 1493 dwellings times 48 data-points per day).

[2] Although ISSDA contacted the authors of the metering project, no answer was obtained about how the data were processed so that all days have 48 data-points.

[3] This is true for the whole year, for spring and autumn, which only contain the longer or shorter day, this slightly affects the average energy demand. These effects are, however, insignificant.

files containing the questions asked in these surveys can be found within the electronic data provided with this thesis.

For Edata, the pre-trial survey was obtained between August and September 2009. It was answered by 3488 residential participants in the trial, and contains the answers to 144 questions (CER, 2011b). For Gdata the pre-trial survey was obtained between April and May 2010. It was answered by 1365 residential participants in the trial, and contains the answers to 156 questions (CER, 2011c). Although Edata contains data for 4255 households, only those with metadata can be used in the projections, therefore the sample is reduced to 3488 households. The same happens with Gdata, where the projectable data shrink from 1493 to 1365.

6.2.3 Comparison with UK

As stated in the Chapter 5, projections present the evolution the given data follow by varying a variable as in a particular scenario. However, on top of the information about the evolution of the data's behaviour, the more representative the data are of a certain domain, the more informative the outcome of the projection will be. Therefore, as the projections are obtained into scenarios which represent urban UK, it is important to investigate the representativeness of the households in the samples and their energy demand in respect to the UK.

The average household size in 2010 UK (2.35) was smaller than that of the samples (Edata: 2.71, Gdata: 2.87)[4]. The average electricity demand per household in Edata is quite similar to that in UK (Edata: 4400 kWh/household; UK: 4356 kWh/household). However, the average electricity demand per person is lower in the sample (Edata: 1624 kWh/person, UK: 1918 kWh/person). In the case of gas, the averages are very different to those in UK for both, per household demand (Gdata: 7819 kWh/household; UK: 13181 kWh/household) and per person demand (Gdata: 2727 kWh/person, UK: 5609 kWh/person). There is no clear explanation for this huge difference between the gas demand in Gdata and that in UK. In general, the household demand of gas in Ireland is much lower than that of UK, *e.g.* Ireland household's demand of gas in 2016 was around 3970 kWh/household (SEAI, 2018). However, this is, at least in part, due to the high use of other energy sources —like oil— that a meaningful part of Irish households use for their heating systems instead of (or in addition to) gas. This effect is not present in Gdata, where almost 100% of the households use gas for space heating. A possible explanation of the lower demand of gas in Gdata is that the average dwelling floor are is smaller in Ireland (81 m^2 (Hennigan, 2018)) than in UK (91.2 m^2 (DCLG, 2010)). The total energy demand

[4]The surveys ask for the amount of adults (>15) and non-adults (<15) in the dwellings. The highest answer is '7 or more'. This answer could introduce uncertainty in the amount of occupants each dwelling has. In both samples there are dwellings with 7 or more adults. These are, however, only 7 in Edata and 3 in Gdata. No sample contains dwellings with 7 or more occupants under 15. This means that the uncertainty in the answers of this question is minimal.

of UK households has been retrieved from (BEIS, 2018a) while the average household size and total population was found in (Palmer & Cooper, 2013).

Comparing the distribution of types of buildings, the ratio of semi-detached houses is higher in the data samples (Edata: 0.30, Gdata: 0.54) than in UK (0.25), especially in Gdata. Detached houses are much more present in Edata (0.54) than in UK (0.26) or Gdata (0.21), which are quite similar. Terraced houses and flats are more present in UK (0.29 and 0.19 respectively) than in the samples (Edata: 0.14, 0.02; Gdata: 0.21, 0.02). The data from UK were retrieved from (DCLG, 2011).

These broad comparisons show that the data samples do not seem representative of UK. This implies that their projections into UK scenarios will provide the evolutions household energy demand would have in the different scenarios but the resulting values will not be representative of the UK household energy demand in these scenarios. These evolutions can, then, be applied to UK household energy demand to define the possible paths this energy demand could take into the future.

6.3 Managing the data

The software MATLAB was used to manage the data and to produce the projections for *EVERYTHING* (see Section 6.1 for the definition of *EVERYTHING*) with both data samples. Several scripts and functions were developed to that end. First, the data had to be opened and stored in a format which was easy to work and do calculations with. Then, the energy demand for the samples and the projections could be calculated. The actual sample of households used for each projection depended on the answers to the surveys, and the ratios and energy demands of the groups, which are different for different variables, had to be obtained as well. An unexpected difficulty was the management of this plethora of values. The actual calculations to obtain projections are rather straightforward, they only consist in weighted sums, sometimes corrected with factors. However, for each calculation the precise values had to be accessed, and the data samples and results had to be organised in a way which is easy to understand in order to minimise errors and facilitate comprehension of eventual users. Following there is a review of the scripts and functions used to manage the data and obtain the projections.

importmydata.m: script that opens the different files with energy demand data and concatenates them in 2 huge matrices, one for electricity and one for gas (these are mainly what Edata and Gdata refer to). The values are divided by 2 to make them kWh (they are expressed in kW in the files provided by the ISSDA), the data are ordered first by ID and then by time. Then, it also puts the metada in 2 matrices (one for electricity and one gas) in a convenient format. It also generates a column vector with the summary of the questions answered in the metadata to facilitate their management. For Edata, it keeps only the IDs which the allocations file associates to households (in Gdata they are all households because ISSDA sent only these data) and had responded the survey —not all the households for which there is data had done so—.

timedecoder.m: script that adds two columns to Edata and Gdata, one corresponding to the day and the other corresponding to the half an hour period which are coded in the "date code" (column 2). This is to facilitate the posterior handling of the data.

metadata.m: script that operates with the answers of the surveys which give relevant information for grouping the households for each variable. It produces two matrices with the relevant metadata, one for Edata and one for Gdata; the rows correspond to each ID which had answered the pre-trial survey and each column corresponds to one of the variables projected (except the first one, which contains the ID number of the row). For a given ID, the number in each row conveys the group in which that ID falls for the given variable. When an ID does not belong to any group for a given variable a NaN (Not a Number) is introduced. The script also produces two other matrices with headings for the metadata relevant for Edata and Gdata. These headings convey the name of the variable of each column and that of their groups in different iterations (some names and groups have evolved and it was convenient to keep them like this).

idperiodaverage.m: function that finds the total energy, daily average energy per household, and daily average energy per person of the different groups and period of days inputted. It also finds the total energy demanded by all the IDs inputted, but this data are not used in posterior steps. In addition, it also returns the average household size. It needs as input a cell array with the IDs of each group, a vector with the days to average, the data (Edata or Gdata) and the metadata file to obtain the average household size.

dayprofile.m: function that returns an array with 48 values per column which correspond to the average electricity consumed by each group of households (and per person) in each of the 48 half an hour periods of the days in a given period. It needs to input a cell array with the IDs of each group, a vector with the days to average, the data (Edata or Gdata) and the average household size to obtain the values per person.

project.m: function that produces projections for *EVERYTHING* with the data inputted. To do so, it needs to get as input the variable number (corresponding to the column number in metadata), a variable conveying whether the data are Edata or Gdata, the data, and the weights of the groups. It invokes *idperiodaverage.m* and *dayprofile.m* to obtain the daily averages and daily profiles. It projects FWr and FWp separately and obtains FW summing them with the appropriate weights. It returns a struct array (particular type of array in the MATLAB environment which can contain any type of data and they can be mixed) with the following fields: variable name; all results for total daily average energy demand in a cell comparing the energy demand in the data, that of NSP, PR, MF, FW, FWr, FWp, and that of each group (for AD, WD, WE; per household and per person; and for all periods); the results of all projections for *EVERYTHING*; the ratios of each group (called frequencies for historical reasons); the base data for *EVERYTHING*; the same for the rich (social classes A and B); the same for the poor (other social classes); the weighted averages for *EVERYTHING* of the different groups without adding them up; and the weights of each group. It also produces several plots comparing the daily profiles of the base sample and scenarios, and the different groups in the base sample (also for the different types of day). The main challenge of this function was to manage all the data and results in a coherent and understandable way. The calculations, which come from Section 5.4 are straightforward and could be easily validated by doing the calculations with Excel for different representative sub-samples. There needed to be two versions of this function. Besides the general one, a mirror of the function with a small change was needed to project the variable 'Energy purchasing power', *projectNaN.m*. This is because for this variable the groups already separate the poor and the rich, which needed to be taken in to account.

projectall.m: simple function that needs a single input indicating if the projections for Edata or for Gdata are sought. It contains all the variable numbers for which each data can be projected, and it opens the data and weights automatically. It invokes *project.m* (and the mirror function for 'Energy purchasing power') and generates a struct array with all the results.

Besides these scripts and functions, some matrices have also been produced to convey some information needed for them to work. Edata, Gdata, both metadata, and both metadata headers (arrays with the 'headers' explaining to what variable each metadata column belongs to, and the grouping criteria used to define the groups) have been combined in a single cell array for ease of use, *EGdata.mat*; a cell array containing the day numbers of the different periods (for AD, WD and WE) was produced, *Days.mat*; and a cell array with the ratios and the corrections for each household group in each variable was also produced, *Weights.mat* —these are the weights opened by *projectall.m* and used by *project.m*—. Find all these files within the electronic data provided with this thesis (see Appendix D).

Note that MATLAB is a numerical computing environment and proprietary programming language, therefore one needs a license in order to use it. Universities do normally own licences to use MATLAB, which are usually available for staff and students. However, if one does not have access to a license, GNU Octave is a free open source alternative to MATLAB which can, in principle, be used to compile and use these functions, scripts and arrays. GNU Octave aims to be drop-in compatible with MATLAB's syntax, however not all MATLAB functions are available in GNU Octave. This means that it is possible —although not probable— that some error arises when using the previously described files in GNU Octave.

6.4 Brief analysis of the samples' energy demand

Projections show the behaviour of the samples' energy demand when a particular variable follows the characteristics of a given scenario. In order to know the evolution of that energy demand, one has to be familiar with its behaviour in the base scenario; in this case, the behaviour of the energy demand of Edata and Gdata. Therefore, it is important to analyse these energy demands in the different forms the projections take, *i.e.* for *EVERYTHING*, to have a benchmark for the projections and see their evolution.

Note that not all projections use exactly the same base data. This happens mostly because not all the households were able to answer all the questions in the survey. In addition, sometimes, some households did not fit to any of the groups defined and could not be used. These differences in the base data are not significant except for the variable 'Space heating' in Edata. This is a general analysis; however, in the sub-sections of 'Development and projection of variables', Section 6.5, when groups are defined there are further analyses of the particularities of the energy demand of these groups.

The electricity demand per household of Edata in the different periods can be seen in Figure 6.4.0.1. They follow a common daily electricity profile which is flatter when it is hot (as expected for data from Ireland where there is no need of cooling) and peakier when it is cold. With one large peak in the evening, a secondary one around noon, and a large valley during the night. One can also see how in WE the morning increase in electricity demand starts later but is higher and stays higher for the rest of the day. This produces a significantly larger demand of electricity in WE than in WD, see Table 6.4.0.1. This increase in the electricity demand during WE is much larger when the weather is cold than when it is warm. The electricity demand per person is not showed because the household size does not change (it is 2.7), therefore the plot would look exactly the same but with electricity values 2.7 times smaller.

Table 6.4.0.1: Average daily electricity demand per household and per person by type of day for the different periods.

(kWh)	Annual	Winter	Spring	Summer	Autumn	Hottest	Coldest	Comp.
AD	11.94	14.30	11.31	10.32	11.86	– –	– –	12.16
	4.42	5.29	4.19	3.82	4.39	– –	– –	4.50
WD	11.73	14.08	11.12	10.21	11.58	9.97	15.28	11.89
	4.34	5.21	4.12	3.78	4.29	3.69	5.66	4.40
WE	12.46	14.84	11.79	10.63	12.58	10.22	16.79	12.86
	4.61	5.50	4.37	3.94	4.66	3.78	6.22	4.76

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person. Comp. refers to the comparing season which for Edata is autumn 2009.
AD, WD, WE stand for All Days, Week Days, WeekEnd days.

The gas demand per household of Gdata in the different periods can be seen in Figure 6.4.0.2. They follow a common daily gas profile with two clear peaks, a larger one in the evening and a smaller one in the morning. In WE the morning peak is slightly later —but less than for Edata—, it is smaller and after the peak there is no valley (people are much

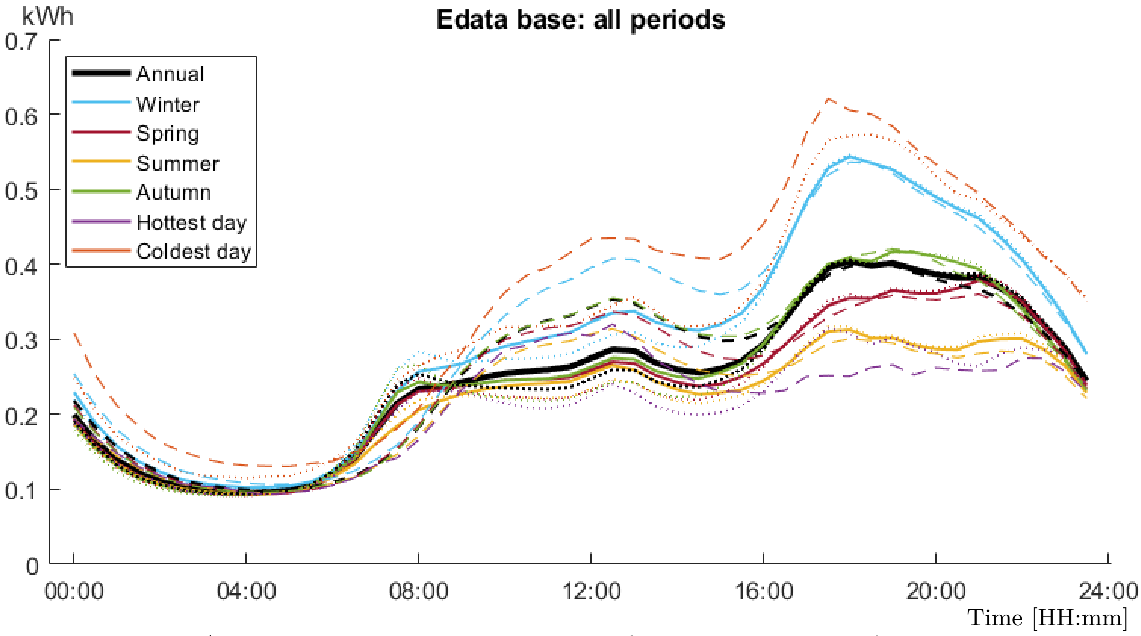


Figure 6.4.0.1: Average daily energy demand profile per household of Edata in all periods of time. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

more likely to stay at home). This makes the gas demand in WE, on average, slightly larger. However, it is only larger when it is colder (winter and autumn) and slightly smaller when is hotter (summer and spring), see Table 6.4.0.2. As seen in Section 6.2.3, there is a higher average energy demand of gas than of electricity. Gas also shows much more variability: in summer the demand for gas is much lower than the average, in winter the difference with the average is even larger (in the opposite direction), and the demand of the coldest days is still much higher than that of the winter as a whole. This is likely to be due to the small percentage of households using electric heating plus the small effect it has —see Section 6.5.7—. The gas demand per person is not shown for the same reason as the electricity demand per person.

Table 6.4.0.2: Average daily gas demand per household and per person by type of day for the different periods.

(kWh)	Annual	Winter	Spring	Summer	Autumn	Hottest	Coldest	Comp.
AD	21.66	43.39	20.50	3.58	19.52	– –	– –	40.13
	7.55	15.13	7.15	1.25	6.81	– –	– –	13.99
WD	21.63	43.01	21.13	3.62	19.20	2.85	61.52	39.89
	7.54	15.00	7.37	1.26	6.70	0.99	21.46	13.91
WE	21.74	44.31	18.89	3.49	20.27	3.24	64.42	40.71
	7.58	15.45	6.59	1.22	7.07	1.13	22.47	14.20

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person. Comp. refers to the comparing season which for Gdata is winter 2010-11.

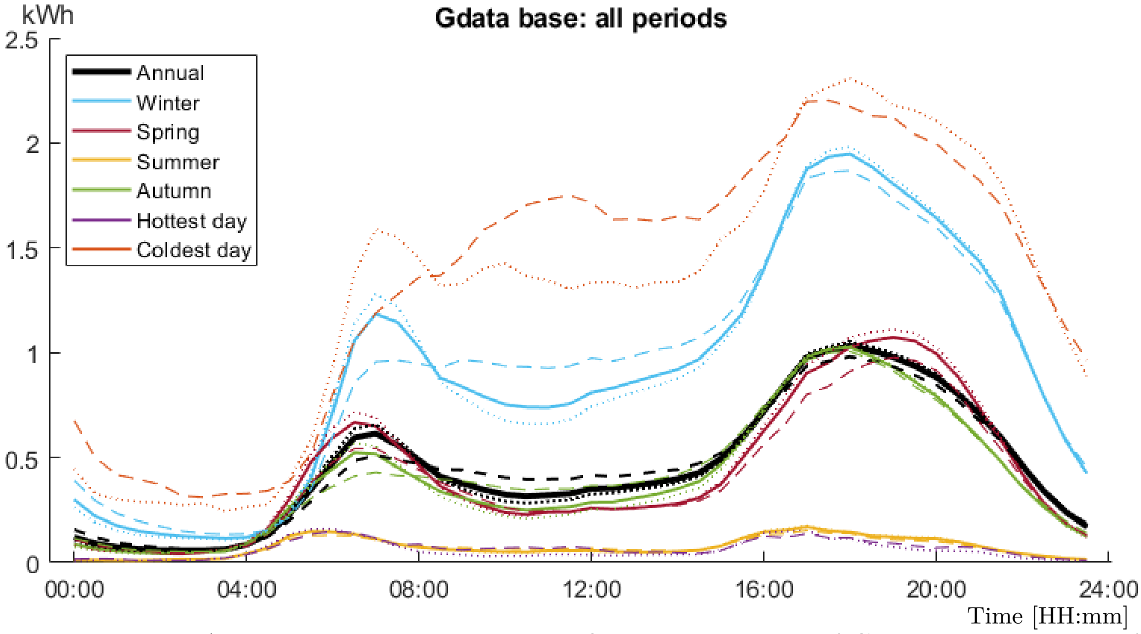


Figure 6.4.0.2: Average daily gas demand profile per household of Gdata in all periods of time. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

6.5 Development and projections of variables

In each subsection here, each variable is first defined and developed, and subsequently the relevant data projected with the framework developed in the previous chapter, *i.e.* the tool is used to project the relevant data for each variable. The data projected is mostly both Edata and Gdata but, as seen in Table 6.1.0.3, some variables only apply to one of them. The first step consists of fine tuning the definition of the variable to make it compatible with the metadata and the relevant indicators from the extended DRC. This is, however, not always needed. Then, the factors needed to obtain the projection are developed based on the metadata, on the characteristics of the relevant indicators and, sometimes, also on other relevant literature. Finally the projection for the average annual energy demand is shown and analysed. The tables with the results of the projections for the daily averages in the other time periods can be found in Appendix C.1. They are not showed here because the factors found for each projection are constants; they do not vary in time. Therefore, the evolution followed by the data is the same in all of the periods.

In the cases where group ratios have to be derived for the future scenarios, the process used to do it entails the following: modify the base ratio of a group (from the base scenario, Edata or Gdata depending on the context) following the characteristics of that group in the future scenario. Do the same successively with all groups. At this point, the values of the groups' ratios are unlikely to add up to 1. Therefore, further iterations are normally needed to derive the definitive values, which must add up to 1 and follow the characteristics of the scenario.

Tables 6.5.0.1 and 6.5.0.2 show a review of the groups, base scenario ratios, sample ratios and future scenario factors (ratios, corrections) defined/found for each variable and data sample. In the cases where groups were defined, the following values are shown in line with the group definition: the group ratios in the base, data sample and future scenarios, and/or their corrections. When it is not clear what the definition of the groups refers to, a short description is given (between brackets) below the variable's name.

Table 6.5.0.1: Review of groups, ratios and corrections for Edata (continued on next page).

<table>
<tr><th rowspan="2">Variable</th><th rowspan="2">Groups</th><th>Base</th><th>Edata</th><th colspan="2">NSP</th><th colspan="2">PR</th><th colspan="2">MF</th><th colspan="2">FWp|FWr</th></tr>
<tr><th>scenario</th><th>ratios</th><th>f_i/F</th><th>k_i/k</th><th>f_i/F</th><th>k_i/k</th><th>f_i/F</th><th>k_i/k</th><th>f_i/F</th><th>k_i/k</th></tr>
<tr><td>Number of households</td><td>–</td><td>25.8</td><td>–</td><td>0.61</td><td>–</td><td>1.08</td><td>–</td><td>1.32</td><td>–</td><td>0.60</td><td>–</td></tr>
<tr><td>Attitudes to energy efficiency & sustainability</td><td>–</td><td>–</td><td>–</td><td>–</td><td>0.50</td><td>–</td><td>0.75</td><td>–</td><td>1.40</td><td>–</td><td>1.40|1.20</td></tr>
<tr><td>Energy efficiency of appliances</td><td>–</td><td>–</td><td>–</td><td>–</td><td>0.62</td><td>–</td><td>0.62</td><td>–</td><td>1.05</td><td>–</td><td>0.90</td></tr>
<tr><td rowspan="4">Percentage of children in the household</td><td>0%</td><td rowspan="4">–</td><td>0.73</td><td>0.81</td><td rowspan="4">–</td><td>0.78</td><td rowspan="4">–</td><td>0.77</td><td rowspan="4">–</td><td>0.62|0.38</td><td rowspan="4">–</td></tr>
<tr><td>$< 50\%$</td><td>0.12</td><td>0.14</td><td>0.11</td><td>0.11</td><td>0.15|0.28</td></tr>
<tr><td>50%</td><td>0.09</td><td>0.04</td><td>0.07</td><td>0.08</td><td>0.17|0.20</td></tr>
<tr><td>$> 50\%$</td><td>0.06</td><td>0.01</td><td>0.03</td><td>0.04</td><td>0.06|0.14</td></tr>
<tr><td rowspan="5">Energy purchasing power (social class)</td><td>AB</td><td>0.27</td><td>0.15</td><td>0.16</td><td>1</td><td>0.24</td><td>1</td><td>0.21</td><td>1</td><td>0.13</td><td>1</td></tr>
<tr><td>C1</td><td>0.28</td><td>0.27</td><td>0.52</td><td>1</td><td>0.32</td><td>1</td><td>0.14</td><td>1</td><td>0.01</td><td>1</td></tr>
<tr><td>C2F</td><td>0.20</td><td>0.20</td><td>0.19</td><td>1</td><td>0.21</td><td>1</td><td>0.10</td><td>1</td><td>0.02</td><td>0.94</td></tr>
<tr><td>D</td><td>0.15</td><td>0.05</td><td>0.02</td><td>1</td><td>0.04</td><td>1</td><td>0.05</td><td>1</td><td>0.06</td><td>0.86</td></tr>
<tr><td>E</td><td>0.10</td><td>0.33</td><td>0.11</td><td>1</td><td>0.19</td><td>1</td><td>0.49</td><td>1</td><td>0.78</td><td>0.69</td></tr>
<tr><td rowspan="3">Space heating</td><td>Electricity</td><td>0.09</td><td>0.07</td><td>0.29</td><td rowspan="3">–</td><td>0.47</td><td rowspan="3">–</td><td>0.22</td><td rowspan="3">–</td><td>0.15|0.04</td><td rowspan="3">–</td></tr>
<tr><td>Gas(&non-el.)</td><td>0.81</td><td>0.93</td><td>0.71</td><td>0.53</td><td>0.78</td><td>0.85|0.96</td></tr>
<tr><td>Other</td><td>0.10</td><td>–</td><td>–</td><td>–</td><td>–</td><td>–</td></tr>
<tr><td rowspan="4">Type of building</td><td>Flat</td><td>0.20</td><td>0.02</td><td>0.17</td><td rowspan="4">–</td><td>0.16</td><td rowspan="4">–</td><td>0.04</td><td rowspan="4">–</td><td>0.01|0.11</td><td rowspan="4">–</td></tr>
<tr><td>Semi-detached</td><td>0.28</td><td>0.30</td><td>0.24</td><td>0.21</td><td>0.32</td><td>0.35|0.26</td></tr>
<tr><td>Detached</td><td>0.23</td><td>0.54</td><td>0.46</td><td>0.46</td><td>0.56</td><td>0.60|0.42</td></tr>
<tr><td>Terraced</td><td>0.29</td><td>0.14</td><td>0.13</td><td>0.17</td><td>0.08</td><td>0.04|0.21</td></tr>
</table>

Table 6.5.0.1 – *Continued from previous page*

Variable	Groups	Base scenario	Edata ratios	NSP		PR		MF		FWp|FWr	
				f_i/F	k_i/k	f_i/F	k_i/k	f_i/F	k_i/k	f_i/F	k_i/k
Number of bedrooms	1	–	0.01	0.01	0.95	0.11	0.95	0.16	1	0.04|0.31	1.3|0.8
	2		0.08	0.04		0.16		0.19		0.09|0.36	
	3		0.44	0.41		0.43		0.17		0.28|0.21	
	4		0.35	0.39		0.25		0.28		0.35|0.11	
	5+		0.11	0.15		0.05		0.20		0.24|0.01	
Appliances ownership and use (appliance points)	$(-\infty, 10]$	–	0.11	0.51	–	0.09	–	0.04	–	0.01|0.91	–
	$(10, 20]$		0.42	0.39		0.46		0.32		0.24|0.08	
	$(20, 30]$		0.32	0.09		0.34		0.41		0.43|0.01	
	$(30, 40]$		0.11	0.01		0.09		0.14		0.19|0.00	
	$(40, \infty)$		0.04	0.00		0.02		0.09		0.13|0.00	
Energy poverty	Energy poor	0.11	0.10	0.00	–	0.01	–	0.10	–	0.00|1.00	–
	No energy poor	0.89	0.90	1.00		0.99		0.90		1.00|0.00	
Household size	1	–	0.21	0.13	–	0.23	–	0.26	–	0.18|0.07	–
	2		0.33	0.24		0.34		0.36		0.33|0.17	
	3		0.17	0.22		0.17		0.18		0.20|0.23	
	4		0.16	0.20		0.15		0.15		0.21|0.22	
	5		0.08	0.13		0.08		0.04		0.06|0.18	
	6+		0.04	0.08		0.03		0.01		0.02|0.13	

Table 6.5.0.2: Review of groups, ratios and corrections for Gdata (continued on next page).

<table>
<tr><th rowspan="2">Variable</th><th rowspan="2">Groups</th><th>Base</th><th>Gdata</th><th colspan="2">NSP</th><th colspan="2">PR</th><th colspan="2">MF</th><th colspan="2">FWp|FWr</th></tr>
<tr><th>scenario</th><th>ratios</th><th>f_i/F</th><th>k_i/k</th><th>f_i/F</th><th>k_i/k</th><th>f_i/F</th><th>k_i/k</th><th>f_i/F</th><th>k_i/k</th></tr>
<tr><td>Number of households</td><td>–</td><td>25.8</td><td>–</td><td>0.61</td><td>–</td><td>1.08</td><td>–</td><td>1.32</td><td>–</td><td>0.60</td><td>–</td></tr>
<tr><td>Attitudes to energy efficiency & sustainability</td><td>–</td><td>–</td><td>–</td><td>–</td><td>0.50</td><td>–</td><td>0.75</td><td>–</td><td>1.40</td><td>–</td><td>1.40|1.20</td></tr>
<tr><td>Energy efficiency of dwellings</td><td>–</td><td>–</td><td>–</td><td>–</td><td>0.65</td><td>–</td><td>0.70</td><td>–</td><td>0.95</td><td>–</td><td>0.90|0.95</td></tr>
<tr><td rowspan="4">Percentage of children in the household</td><td>0%</td><td rowspan="4">–</td><td>0.64</td><td>0.73</td><td rowspan="4">–</td><td>0.72</td><td rowspan="4">–</td><td>0.70</td><td rowspan="4">–</td><td>0.60|0.33</td><td rowspan="4">–</td></tr>
<tr><td>< 50%</td><td>0.16</td><td>0.18</td><td>0.14</td><td>0.14</td><td>0.19|0.29</td></tr>
<tr><td>50%</td><td>0.13</td><td>0.08</td><td>0.11</td><td>0.12</td><td>0.16|0.24</td></tr>
<tr><td>> 50%</td><td>0.07</td><td>0.01</td><td>0.03</td><td>0.04</td><td>0.05|0.14</td></tr>
<tr><td rowspan="5">Energy purchasing power (social class)</td><td>AB</td><td>0.27</td><td>0.25</td><td>0.24</td><td>1</td><td>0.35</td><td>1</td><td>0.36</td><td>1</td><td>0.28</td><td>1</td></tr>
<tr><td>C1</td><td>0.28</td><td>0.30</td><td>0.52</td><td>1</td><td>0.32</td><td>1</td><td>0.17</td><td>1</td><td>0.01</td><td>0.92</td></tr>
<tr><td>C2F</td><td>0.20</td><td>0.20</td><td>0.17</td><td>1</td><td>0.19</td><td>1</td><td>0.11</td><td>1</td><td>0.03</td><td>0.80</td></tr>
<tr><td>D</td><td>0.15</td><td>0.04</td><td>0.01</td><td>1</td><td>0.03</td><td>1</td><td>0.04</td><td>1</td><td>0.06</td><td>0.73</td></tr>
<tr><td>E</td><td>0.10</td><td>0.21</td><td>0.06</td><td>1</td><td>0.11</td><td>1</td><td>0.33</td><td>0.86</td><td>0.63</td><td>0.60</td></tr>
<tr><td rowspan="3">Space heating</td><td>Electricity</td><td>0.09</td><td>–</td><td rowspan="3">0.05</td><td rowspan="3">–</td><td rowspan="3">0.19</td><td rowspan="3">–</td><td rowspan="3">0.86</td><td rowspan="3">–</td><td rowspan="3">0.79|0.06</td><td rowspan="3">–</td></tr>
<tr><td>Gas(&non-el.)</td><td>0.81</td><td>~1.0</td></tr>
<tr><td>Other</td><td>0.10</td><td>–</td></tr>
<tr><td rowspan="4">Type of building</td><td>Flat</td><td>0.20</td><td>0.02</td><td>0.18</td><td rowspan="4">–</td><td>0.17</td><td rowspan="4">–</td><td>0.05</td><td rowspan="4">–</td><td>0.01|0.11</td><td rowspan="4">–</td></tr>
<tr><td>Semi-detached</td><td>0.28</td><td>0.55</td><td>0.46</td><td>0.42</td><td>0.58</td><td>0.59|0.45</td></tr>
<tr><td>Detached</td><td>0.23</td><td>0.21</td><td>0.16</td><td>0.17</td><td>0.25</td><td>0.31|0.15</td></tr>
<tr><td>Terraced</td><td>0.29</td><td>0.21</td><td>0.20</td><td>0.24</td><td>0.14</td><td>0.09|0.28</td></tr>
</table>

Table 6.5.0.2 – *Continued from previous page*

Variable	Groups	Base scenario	Gdata ratios	NSP		PR		MF		FWp|FWr	
				f_i/F	k_i/k	f_i/F	k_i/k	f_i/F	k_i/k	f_i/F	k_i/k
Number of bedrooms	1	–	0.01	0.01	0.95	0.11	0.95	0.16	1	0.04|0.31	1.3|0.8
	2		0.09	0.04		0.17		0.20		0.11|0.37	
	3		0.51	0.48		0.49		0.22		0.32|0.23	
	4		0.33	0.37		0.21		0.26		0.31|0.08	
	5+		0.06	0.10		0.02		0.16		0.22|0.01	
Energy poverty	Energy poor	0.11	0.09	0.00	–	0.01	–	0.09	–	0.00|1.00	–
	No energy poor	0.89	0.91	1.00		0.99		0.91		1.00|0.00	
Household size	1	–	0.16	0.09	–	0.17	–	0.20	–	0.19|0.06	–
	2		0.31	0.22		0.32		0.34		0.31|0.17	
	3		0.20	0.23		0.20		0.21		0.22|0.24	
	4		0.21	0.24		0.19		0.19		0.21|0.23	
	5		0.09	0.14		0.09		0.05		0.06|0.18	
	6+		0.04	0.08		0.03		0.01		0.01|0.12	

6.5.1 Number of households

The relevant indicators of the DRC (Lombardi et al., 2012) are 'Total population' and 'Average household size', see their characteristics in Table 6.5.1.1. The characteristics of the first one reveal the total amount of inhabitants in UK in the future scenarios, and these of the second one, give information about the average number of occupants in the households of each scenario relative to the base scenario. Therefore, the change in the number of households can be found for each scenario and affect in the same way both samples (Edata and Gdata).

Table 6.5.1.1: Characteristics of the indicators 'Total population' and 'Average household size' from DRC (Lombardi et al., 2012).

Measure *Base*	NSP	PR	MF	FW
Total population				
	$\Downarrow$	$\Leftrightarrow$	$\Leftrightarrow$	$\Uparrow$ | $\Uparrow$
Million *61.8 (2009 base)*	Total UK population decreases by 11% as compared to 2010 values (UK: 55,002k). Assuming a growth rate of -0.1% per annum from 2010 to 2025 and -0.4% per annum from 2025 to 2050.	Total UK population in 2050 reduces by 1% as compared to 2010 values (UK: 61,184k). Assuming a growth rate of 0.1% per annum from 2010 to 2025 and -0.1% per annum from 2025 to 2050.	Total UK population in 2050 reduces by 1% as compared to 2010 values (UK: 61,184k). Assuming a growth rate of 0.1% per annum from 2010 to 2025 and -0.1% per annum from 2025 to 2050.	Total UK population increases by 3.0% (UK: 63,680k). The ratio of rich to poor is 35:65 (22,288k:41,392k). Assuming a growth rate of 0.2% per annum from 2010 to 2025 and 0.0% per annum from 2025 to 2050.
Average household size				
	$\Uparrow$	$\Leftrightarrow$	$\Downarrow$	$\Downarrow$ | $\Uparrow$
People per household *2.4*	Although population is ageing, strong social and environmental drivers mean co-housing and living with extended family or in multiple family units is commonplace.	Trend towards smaller household sizes continues (exacerbated by ageing population). Core values of individualism mean people do not want to share accommodation.	Trend towards smaller household sizes continues (exacerbated by ageing population). Core values of individualism mean people do not want to share accommodation.	Average household size may increase for the poor out of necessity, and decrease for the rich out of choice.

With the characteristics of the indicator 'Average household size', the average number of occupants per dwelling in each future scenario can be found, and with it and the characteristics of the indicator 'Total population' their number of households. Note that the same can be done with the base scenario, which gives 25.8 M households as a result. Comparing the results for the future scenarios with that for the base scenario the ratio by which the household population changes in each scenario, F^{Sc}, can be easily found. See all these values in Table 6.5.1.2.

Table 6.5.1.2: Household size, number of households, and the ratio by which the household population changes in each scenario.

	NSP	PR	MF	FWr|FWp
Household size	3.5	2.2	1.8	4.1
Number of households	15.7 M	27.8 M	34.0 M	15.5 M
F^{Sc}	0.61	1.08	1.32	0.60

M stands for million.

These changes can be applied to the total energy demand obtained for any projection in order to take into account the change in (household) population of the scenarios. For that, first the energy demand for the whole household population in the base has to be found by multiplying the energy demand per household by the amount of households in the base scenario (25.8 M). Then, the result has to be multiplied by F^{Sc}. This is, obviously, a bit pointless, as one can directly multiply the energy demand per household by the amount of households for each scenario found in Table 6.5.1.2. However, F^{Sc} is found for coherence with the mathematical framework developed in Chapter 5. In Section 6.5.7, where the variable 'Space heating' is developed, another F^{Sc} is found for the change in the household population which uses gas. In that case there is no option to directly find the amount of households which use gas.

6.5.2 Attitudes to energy efficiency and sustainability

The relevant indicator of the extended DRC (Banchs-Piqué et al., 2020) is 'Attitudes to energy efficiency and sustainability', see its characteristics in Table 6.5.2.1. This indicator matches the definition of the variable. The attitudes to energy efficiency and sustainability affect both, electricity and gas demands. Therefore, both samples (Edata and Gdata) can be projected for this variable.

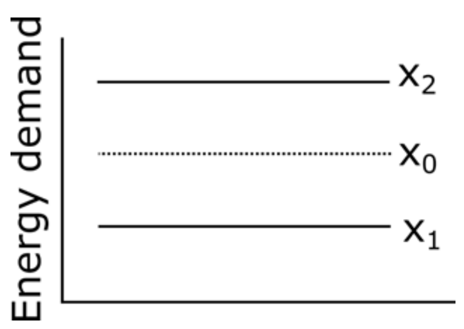
Although the surveys do ask for the respondents' attitudes to energy use (electricity or gas) and their perceived ability to change them, self-reported energy related behaviour is not usually well correlated with energy consumption (Gram-Hanssen, 2014; Huebner et al., 2016). Therefore, as what the variable measures are actual results, there is no information related to this variable in the metadata. However, the indicator describes relative changes (not absolute values) and does not distinguish groups of households, therefore they can be applied to the data as a general correction, k^{Sc}.

Currently, there are large variations in the energy consumed in dwellings. Although these variations are smaller when comparing similar households, they are still very significant. In Morley and Hazas (2011), the factor of difference is found to be between 1.5 and 3, which agrees with that found by other authors, *e.g.* Guerra-Santin et al. (2009). This means that the energy demand of a household can be 3 times larger than that of another very similar household. These differences indicate, in part, how much the energy demand of households is determined by the behaviour of its occupants, and give a benchmark against which the general corrections for this variable can be defined. For the calculation

Table 6.5.2.1: Characteristics of the indicator 'Attitudes to energy efficiency and sustainability' from the extended DRC (Banchs-Piqué et al., 2020).

Attitudes to energy efficiency and sustainability				
Measure *Base*	NSP	PR	MF	FW
	$\Uparrow$	$\Uparrow$	$\Downarrow$	$\Downarrow \mid \Downarrow$
N/A *Some good intentions, less results*	People have the will to be sustainable, the information to be so is widely available and rules and society favour it. The result is a very sustainable society with people willing and able to be sustainable.	People's mindset does not change substantially from the current one. However, the government puts a lot of effort into sustainable measures to make sustainability the default option. Information is reliable and available, making it easier to act sustainably. The result is a society that is more sustainable than currently (but far less than in NSP), in particular the individuals who are engaged.	Sustainability is far from being a priority for the people, rules do not favour it in any special way, information is still poor and confusing and society does not make it easy to be sustainable. There is no big change in society's sustainable attitudes although they worsen, and society makes it as difficult to be sustainable as currently or more. The result is a society that is less sustainable.	Rich: governments try to keep up with sustainability measures, but their priority is security. People, locked up in their enclaves, are not –or do not want to be– aware of the rest of the world. Their attitudes to sustainability are almost nonexistent. Poor: although some –in particular the youth– develop expectations of fairness and may dream of sustainability, they have many more urgent issues to deal with.

to obtain k^{Sc}, the higher end of that factor of difference, 3, is used. It is assumed that current average energy demand (x_0) is in the middle point between those with the highest demand (x_1) and those with the lowest demand (x_1), and that the maximum societal improvements/regressions in attitudes to energy efficiency in the scenarios could shift the average demand to the current lowest/highest consumptions, see Figure 6.5.2.1. These conditions define the system of Equations 6.1.



$x_0 \equiv$ current average demand; $x_1 \equiv$ current lowest demand; $x_2 \equiv$ current highest demand.

Figure 6.5.2.1: Energy demand levels.

This is the system of equations:

$$\begin{cases} x_2 = 3x_1 \\ x_2 - x_1 = 2(x_0 - x_1) \end{cases} \tag{6.1}$$

And these the results:

$$x_2 = \frac{3}{2}x_0\,, \quad x_1 = \frac{1}{2}x_0 \tag{6.2}$$

Therefore, the maximum increase is of 3/2 respect to x_0 (a factor of 1.5) and the maximum decrease of 1/2 (a factor of 0.5). Knowing these extreme values, now the corrections for each scenario (k^{Sc}) can be derived by following the characteristics of the indicator. As the indicator does not distinguish between electricity and gas, the same correction is used for both. The corrections found can be seen in Table 6.5.2.2.

Table 6.5.2.2: Corrections for 'Attitudes to energy efficiency and sustainability'.

	NSP	PR	MF	FWr|FWp
k^{Sc}	0.50	0.75	1.40	1.40|1.20

With these corrections, the projections can be obtained using Expression 5.18. The resulting projections for the annual energy demands are shown in Figures 6.5.2.2 (Edata daily profiles) and 6.5.2.3 (Gdata daily profiles), and in Table 6.5.2.3 (daily averages).

Table 6.5.2.3: Base and projections for annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Attitudes to energy efficiency and sustainability'.

Annual							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	11.94	5.97	8.95	16.71	14.64	19.29	13.94
	4.42	2.21	3.31	6.19	5.42	6.03	5.32
WD	11.73	5.86	8.80	16.42	14.38	18.89	13.71
	4.34	2.17	3.26	6.08	5.32	5.91	5.23
WE	12.46	6.23	9.34	17.44	15.28	20.28	14.53
	4.61	2.31	3.46	6.46	5.65	6.34	5.55
kWh	Totals Gdata						
AD	21.66	10.83	16.24	30.32	27.56	31.66	25.61
	7.55	3.78	5.67	10.58	9.57	10.27	9.17
WD	21.63	10.81	16.22	30.28	27.51	31.55	25.58
	7.54	3.77	5.66	10.56	9.56	10.24	9.16
WE	21.74	10.87	16.31	30.44	27.69	31.90	25.69
	7.58	3.79	5.69	10.62	9.61	10.35	9.20

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

Projections consisting of simple corrections do not leave much room for interpretation. As expected by the corrections found, in PR and particularly in NSP there is a strong decrease in energy demand while in FW and particularly in MF a large increase in energy demand. As no groups are set, the household size stays constant for all the scenarios; therefore, the electricity demand per person differs always by the same factor from the electricity demand per household.

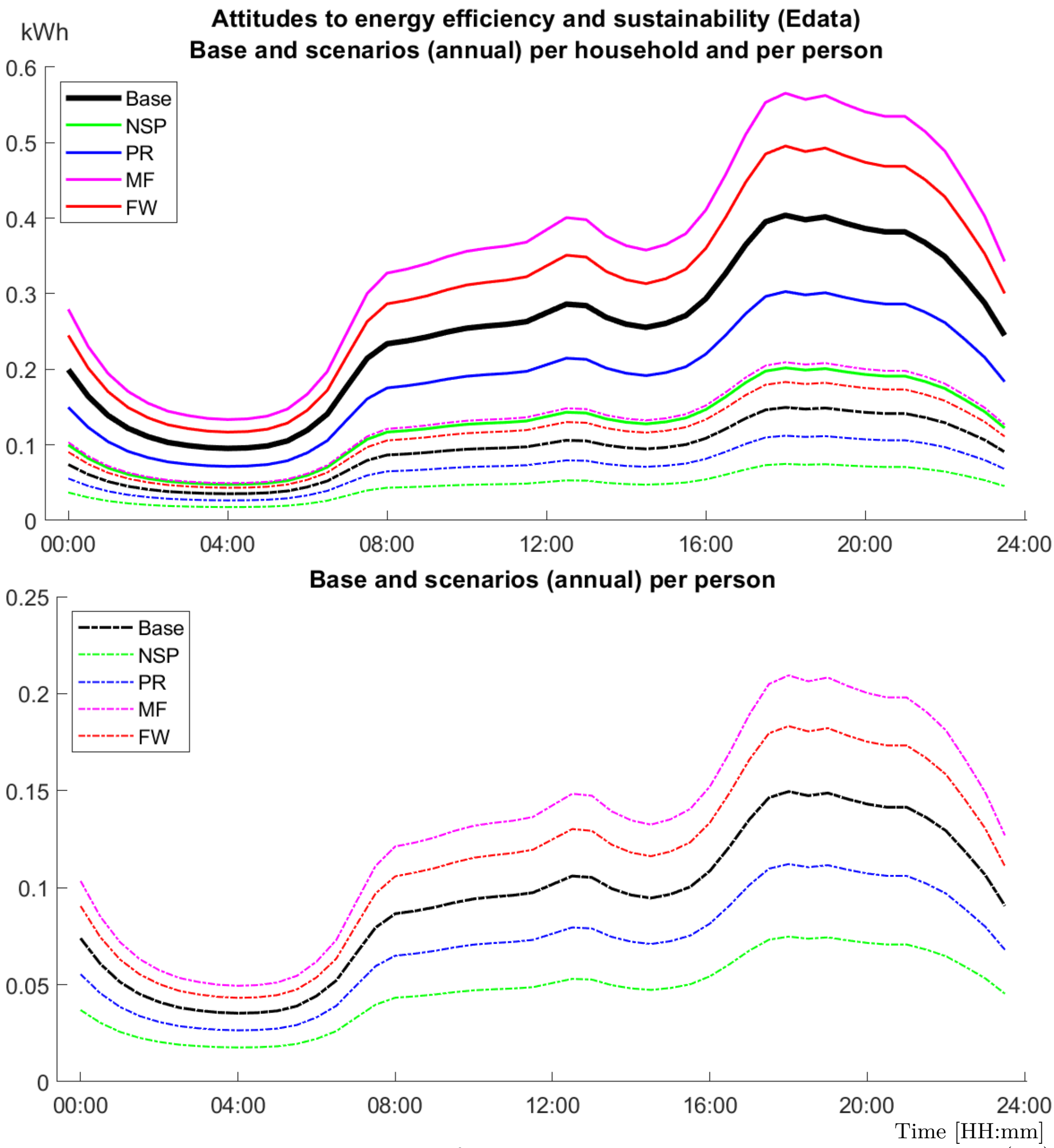


Figure 6.5.2.2: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Attitudes to energy efficiency and sustainability'.

6.5.3 Energy efficiency of appliances

The relevant indicator of the DRC (Lombardi et al., 2012) is 'Energy efficient user technologies', see its characteristics in Table 6.5.3.1. This indicator gives information about at least two independent variables affecting the energy demand of households: appliances (and lights) efficiency, and building efficiency. Here it is only used for the efficiency of the appliances and lights. Appliances are not usually powered by gas, therefore the projection of this variable is only done for Edata.

The metadata of the sample does not convey information about the energy efficiency of the appliances and lights used in the dwellings. However, as the characteristics defined by the indicator are relative (not absolute values), this variable can be taken into account

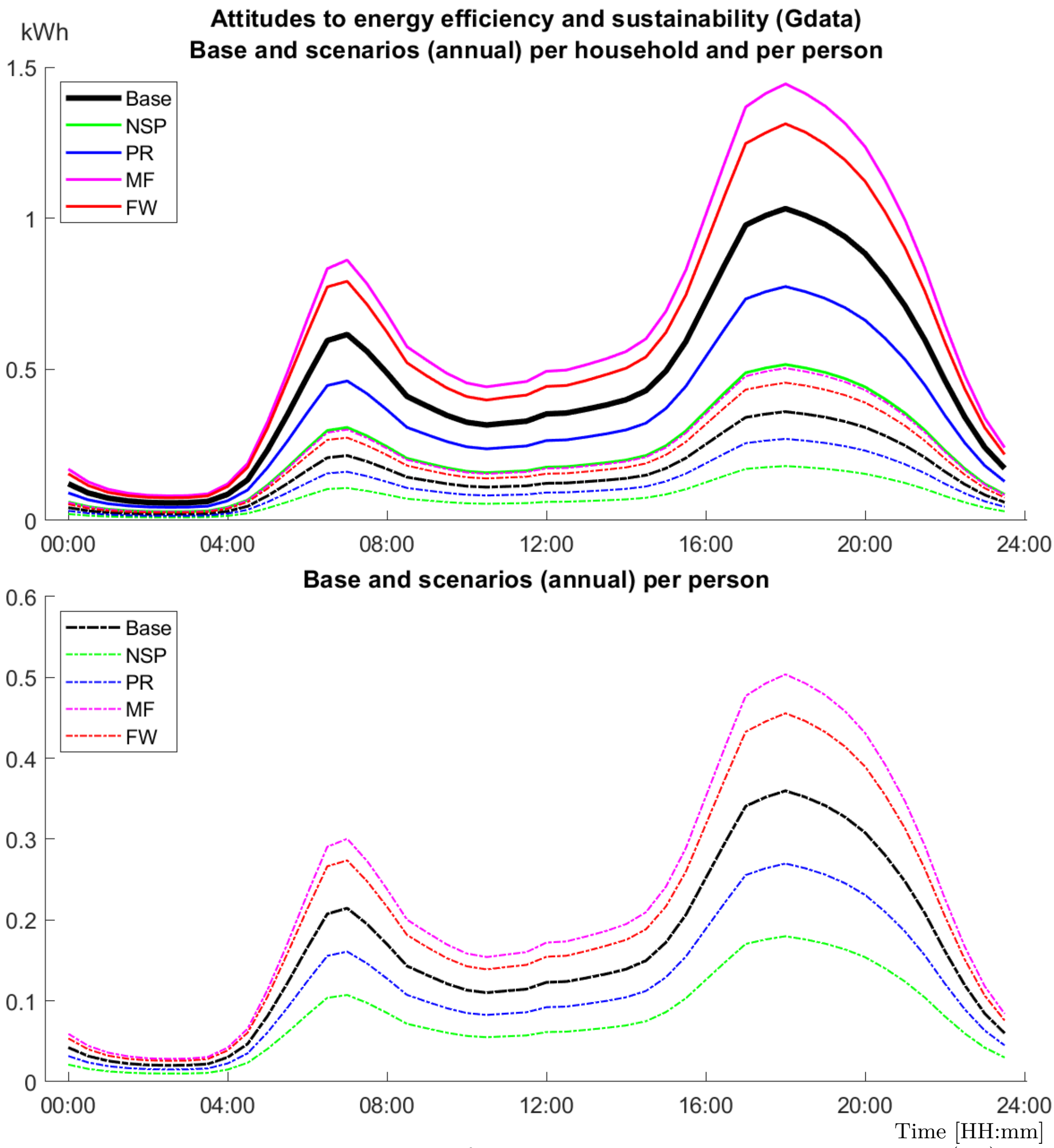


Figure 6.5.2.3: Base and projections of the annual gas demand per household (up) and per person (down) for 'Attitudes to energy efficiency and sustainability'.

with a general correction, k^{Sc}. In order to do this, one needs to search in the literature for information about the energy savings provided by efficient appliances as percentage of the total electricity consumption in the residential sector. In '40% house' (Boardman et al., 2005), it is calculated that around a 44% reduction (compared to 2005 levels) of the electricity consumed by appliances and lights could be achieved. As the data were taken between 2009 and 2010, and the efficiency of appliances has tended to improve, one can assume that the maximum reduction in total electricity consumption due to efficient appliances and lights would be of around 40% compared to the data. With this benchmark and following the characteristics described in the indicator, the change in electricity demand for each scenario can be derived and subsequently expressed as a correction. The correc-

Table 6.5.3.1: Characteristics of the indicator 'Energy efficiency of appliances' from DRC (Lombardi et al., 2012).

Energy efficiency of appliances				
Measure *Base*	NSP	PR	MF	FW
	$\Uparrow$	$\Uparrow$	$\Downarrow$	$\Uparrow \mid \Downarrow$
Percentage of building stock with highest efficiency measures, *e.g.* A++ rating appliances, high thermal insulation, lowest U values etc. (High >60%, Medium 20 to 60%, Low <20%) *Low*	The highest efficiency appliances are adopted. Regulated demands (heating, water heating and lighting) are reduced through improved building fabric (air tightness and high thermal efficiency) and low energy lighting. Energy efficient appliances and renewable supply technologies become widespread. Passive house standards could reduce the heating demands from 160kWh/m^2 to 15kWh/m^2 per year. Renewable offset will depend on technologies adopted and regional parameters (*e.g.* hours sunshine for PV and solar thermal, wind speeds for wind turbines, etc.).	The highest-efficiency appliances are adopted through policy (*e.g.*, through building regulations and planning conditions). The penetration of efficient new technologies is more rapid and widespread. Advanced technologies and building designs (such as passive solar heating, efficient heat pumps and greater direct use of renewable energy) are introduced.	Energy efficiency has improved within industrial sectors but not within domestic/commercial or agriculture.	The rich are adopting technologies, with continued innovation. Technology stagnates for the poor.

tions obtained (and the change in electricity demand that originated them) are presented in Table 6.5.3.2.

Table 6.5.3.2: Change in electricity demand and corresponding correction accounting for the effect of 'Energy efficiency of appliances' for each scenario.

<table>
<tr><th></th><th>NSP</th><th>PR</th><th>MF</th><th>FWr|FWp</th></tr>
<tr><td>Change</td><td>-38%</td><td>-38%</td><td>5%</td><td>-10%|5%</td></tr>
<tr><td>k^{Sc}</td><td>0.62</td><td>0.62</td><td>1.05</td><td>0.90|1.05</td></tr>
</table>

With these corrections, the projections can be obtained using Expression 5.18. The resulting projections for the annual electricity demand are shown in Figure 6.5.3.1 (daily profiles) and Table 6.5.3.3 (daily averages).

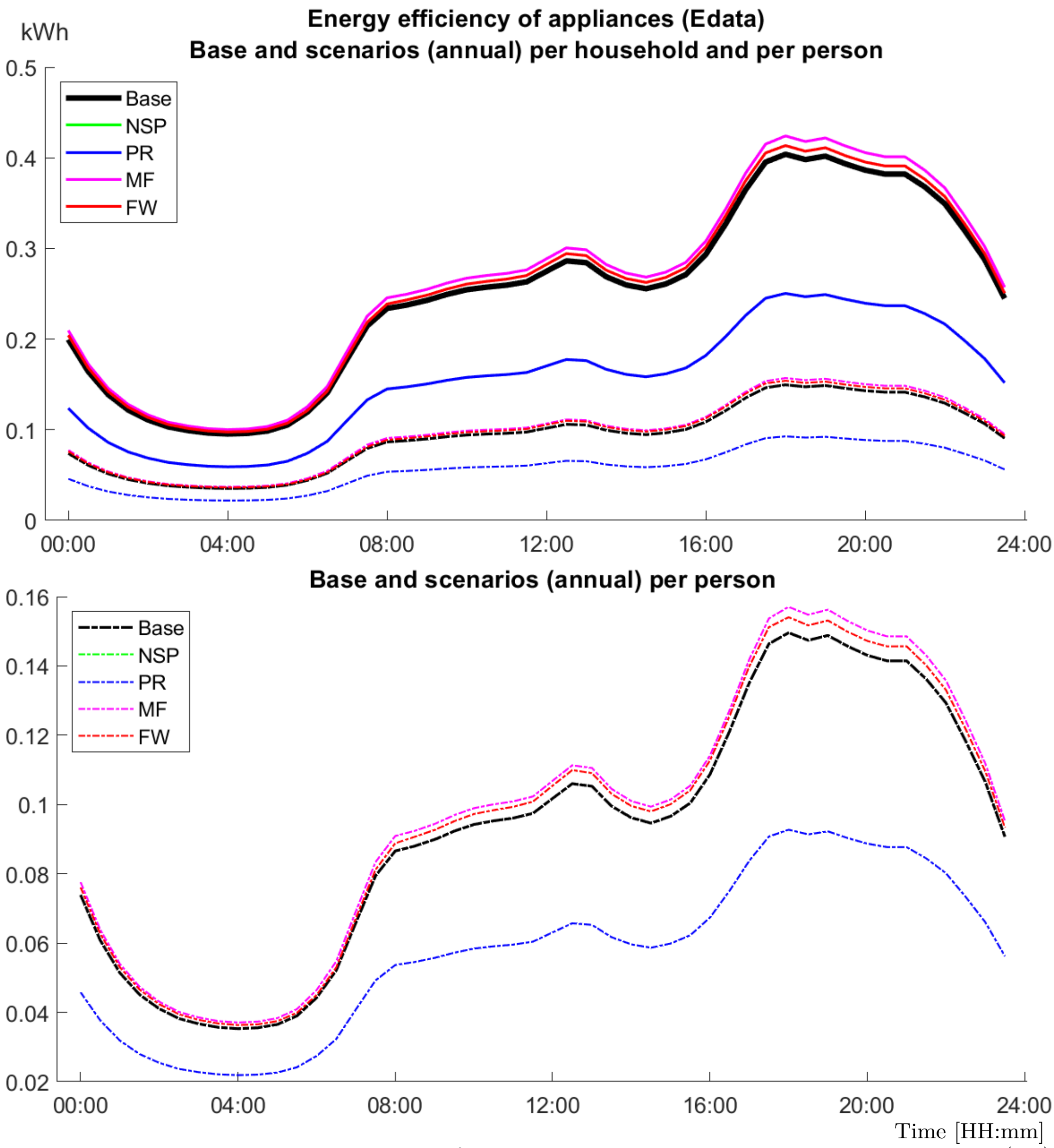


Figure 6.5.3.1: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Energy efficiency of appliances'.

Again, projections consisting of simple corrections do not leave much room for interpretation. Here the projections are obtained only for Edata. As expected, the energy demand in NSP and PR is the same and much lower than that of the base, while these of FW and MF are slightly larger than the base. As no groups are set, the household size stays constant for all the scenarios; therefore, the gas demand per person differs always by the same factor from the gas demand per household.

6.5.4 Energy efficiency of dwellings

The relevant indicator from DRC (Lombardi et al., 2012) is 'Energy efficiency of building and urban morphology', see its characteristics in Table 6.5.4.1.

Table 6.5.3.3: Base and projections for annual average electricity (Edata) demand for the variable 'Energy efficiency of appliances'.

	Annual						
kWh	Totals Edata						
	base	NSP	PR	MF	FW All	FW FWr	FW FWp
AD	11.94	7.40	7.40	12.53	12.22	12.40	12.20
	4.42	2.74	2.74	4.64	4.56	3.88	4.66
WD	11.73	7.27	7.27	12.31	12.01	12.14	11.99
	4.34	2.69	2.69	4.56	4.48	3.80	4.58
WE	12.46	7.72	7.72	13.08	12.76	13.04	12.72
	4.61	2.86	2.86	4.84	4.76	4.08	4.86

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

There is one question in the surveys asking for the Building Energy Rating (BER) of the dwelling (Q455). However, only 42 out of 3488 respondents (1.2%) in Edata, and 66 out of 1365 (4.8%) in Gdata have (or know that they have) a BER. This would constitute a very small sample of households with low significance. However, there are other questions related to the efficiency of the dwellings (Q4905, Q4906, Q4907, Q4908, Q4909). In order to define the groups of households, a punctuation system has been set. The points are set as follows:

Q4906 – Approximate proportion of windows which are double glazed: None = 0; About a quarter = 0.25; About half = 0.5; About three quarters = 0.75; All = 1.

Q4907 – Does your hot water tank have a lagging jacket? No = 0; Yes = 1.

Q4908 – Is your attic insulated? Since when? No=0; Yes, since more than 5 years = 0.75; Yes, new = 1; Don't know = NaN.

Q4909 – Are the external walls of your home insulated? No = 0; Yes = 1; Don't know = NaN.

Household's data with answers with NaNs are not used as it would introduce uncertainty. They include 432 (12.4%) of the electric trial, and 217 (16.7%) of the gas trial.

Although the points system gives the same weight to, for example, having the walls insulated and having a lagging jacket, that does not imply that that these provide the same amount of energy efficiency to the dwelling. In addition, the effectiveness of each of these systems greatly depends on the specific conditions of the dwelling and on how well installed they were. Therefore, a simple "counting" punctuation system seemed appropriate: it does not account directly for the energy efficiency of the dwelling but, on average, the dwellings with more points have better energy efficiency than those with less. The punctuation of each question is added up and the groupings are defined as follows: $\{[0,1],(1,2],(2,3],(3,\infty)\}$ (parenthesis, "(" or ")" means the enclosed value is not included

Table 6.5.4.1: Characteristics of the indicator 'Energy efficiency of building and urban morphology' from DRC (Lombardi et al., 2012).

Energy efficiency of building and urban morphology				
Measure *Base*	NSP	PR	MF	FW
	⇑	⇑	⇔	⇔ | ⇓
U values (W/m^2K) Walls, roofs and floors *0.24*	New buildings have to attain the level 6 of Code for Sustainable Homes, and Passive Solar Principles are used when suitable, to meet per capita greenhouse gas emissions set by global-level agreements. On-site community energy generation units are widely adopted, in the attempt to achieve energy self-sufficiency within each settlement, driven by public preference. It is likely that heating demand reductions go beyond what policy requires. A Passive House does just that by reducing U values for walls, floors and roofs to around 0.1 W/m^2K.	Influenced by climate change goals, mandatory standards are tighter compared to current UK Building Regulations, and technologies improve in response. A percentage of energy use must be met by zero/low carbon energy production. Passive solar principles are recommended in planning policies, but not always used, as they entail strict spatial constraints which, in a world where consumerism is still embedded, may be envisaged as limiting design options and, potentially, financial returns. The mandatory level of energy efficiency corresponds to the one planned for the BR revision of 2013.	Current UK Building Regulations standards are not tightened. Low/zero carbon technologies become more efficient but energy consumption is still quite high as user behaviour is unchanged. Maximised solar access and daylighting is not promoted in planning guidance. It is likely that improvements to building fabric and construction would only occur if very short payback periods could be achieved. Moreover there is no incentive for policies to dictate these measures.	Mandatory building standards have been abolished. Rich residential buildings are built to good standards (UK BR 2010, part L), utilise zero/low carbon technologies, and have good solar access. Poor buildings are built to low standards.

in the group; and bracket, "[" or "]" means the closest value is included in the group). See the distribution of these points for Edata and Gdata, in Figure 6.5.4.1.

As, according to the answers, the absolute majority of the households are already in the highly insulated groups it is not possible to use the ratio-weighted sum to project increases in insulation (there are no data about the energy demand behaviour of better insulated households). However, the data can still be analysed and projections obtained using corrections, k^{Sc}. Table 6.5.4.2 shows the ratios and the daily average energy demand each group present in the data samples.

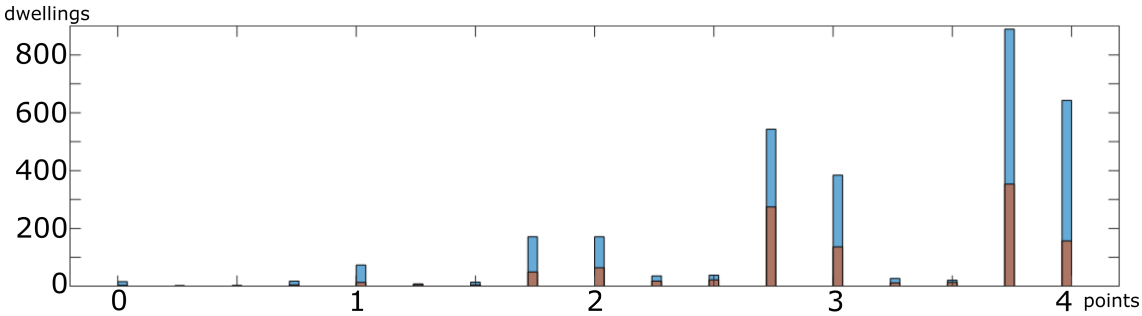


Figure 6.5.4.1: Insulation points distribution. Edata in blue, Gdata in orange.

Table 6.5.4.2: Ratios and average daily energy demand of the different insulation groups.

Group ratios				
Groups	$[0,1]$	$(1,2]$	$(2,3]$	$(3,\infty)$
Edata	0.04	0.12	0.33	0.52
Gdata	0.02	0.11	0.40	0.47
Daily average energy demand (kWh)				
Edata	8.76	10.69	11.73	12.48
Gdata	24.56	22.85	23.20	21.36

It is interesting to see how the energy demand trends are opposing. At the first sight it might be strange that the groups with lower insulation use less electricity than these with better insulation. One has to take into account, however, that (1) not many households use electric heating, (2) for these households, heating is only one part of the total electricity demand, and (3) in this data sample (Edata), the difference in electricity demand between households using electric heating and those not using electric heating systems is surprisingly low (see the projections of 'Space heating', Section 6.5.7). Then, it would make sense that households with less insulated dwellings may be poorer and, therefore, have less appliances and afford to use them less than households which could afford to better insulate their dwellings. However, in the development of 'Energy purchasing power', Section 6.5.6, there is no correlation found between social class and energy demand. Therefore, the reason behind this trend may be another one. In any case, due to the very limited effect that electric heating has in the electricity demand of Edata, which implies that the effect the insulation of the dwelling has is much smaller, the energy efficiency of the dwellings is not projected for Edata.

For Gdata, on the other hand, although the mid-high insulation group demands more energy than the mid-low group, gas demand follows a clear overall downwards trend with higher insulation —as one would expect—. The relation between low and highly insulated groups is of 0.87. With this benchmark and some context information derived from the general narratives of the scenarios, the corrections for each scenario can be derived. See Table 6.5.4.3 for both, the context and the derived corrections.

With these corrections, the projections can be obtained using Expression 5.18. The resulting projections for the annual gas demand are shown in Figure 6.5.4.2 (daily profiles), and in Table 6.5.4.4 (daily averages).

Table 6.5.4.3: Context and corrections for 'Energy efficiency of dwellings' (Gdata).

	NSP	PR	MF	FW
Context	Most new buildings reach passivhaus standard. Old ones are highly retrofitted but most not to passivhaus standards.	Many new buildings reach passivhaus standards, old buildings are mostly retrofitted.	Some improvements with short payback periods are used.	Rich: Some improvements with short payback periods are used plus they can afford better. Poor: The effect to the energy demand of poor households having low efficient dwellings or living in informal settlements is a small decrease in energy demand. This is because the occupants cannot afford to be comfortable anyway, so they do not even try; they simply keep their dwellings colder in winter (and warmer in summer) (Hong, 2011).
k^{Sc}	0.65	0.70	0.95	0.90|0.95

Table 6.5.4.4: Base and projections for annual daily average gas (Gdata) demand for the variable 'Energy efficiency of dwellings'.

Annual							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	21.66	14.08	15.16	20.58	20.50	20.35	20.28
	7.55	4.91	5.29	7.18	7.15	6.60	7.26
WD	21.63	14.06	15.14	20.54	20.47	20.29	20.25
	7.54	4.90	5.28	7.17	7.14	6.58	7.25
WE	21.74	14.13	15.22	20.65	20.59	20.51	20.34
	7.58	4.93	5.31	7.20	7.18	6.66	7.28

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

Again, a projection consisting of simple corrections does not leave much room for interpretation. Here all projections decrease the gas demand. It is mostly because building standards improve, but also because in FWp the worsening of conditions lead to the families not even trying to keep a comfortable temperature at home (see Hong (2011)). As expected, in NSP and PR the gas demand decreases substantially, and in MF and FW it decreases slightly. As the projections consist only of corrections, no groups are set and the household size stays constant for all the scenarios; therefore, the gas demand per person differs always by the same factor from the gas demand per household.

6.5.5 Percentage of children in the household

The relevant indicator from DRC (Lombardi et al., 2012) is 'Age distribution', see its characteristics in the first part of the Table 6.5.5.1. However, the closest information to this indicator appearing in the surveys is the amount of dwelling occupants which are older/younger than 15 years old. The information from the indicator and that from the metadata are not directly related. However, it is possible to derive how the ratio of young

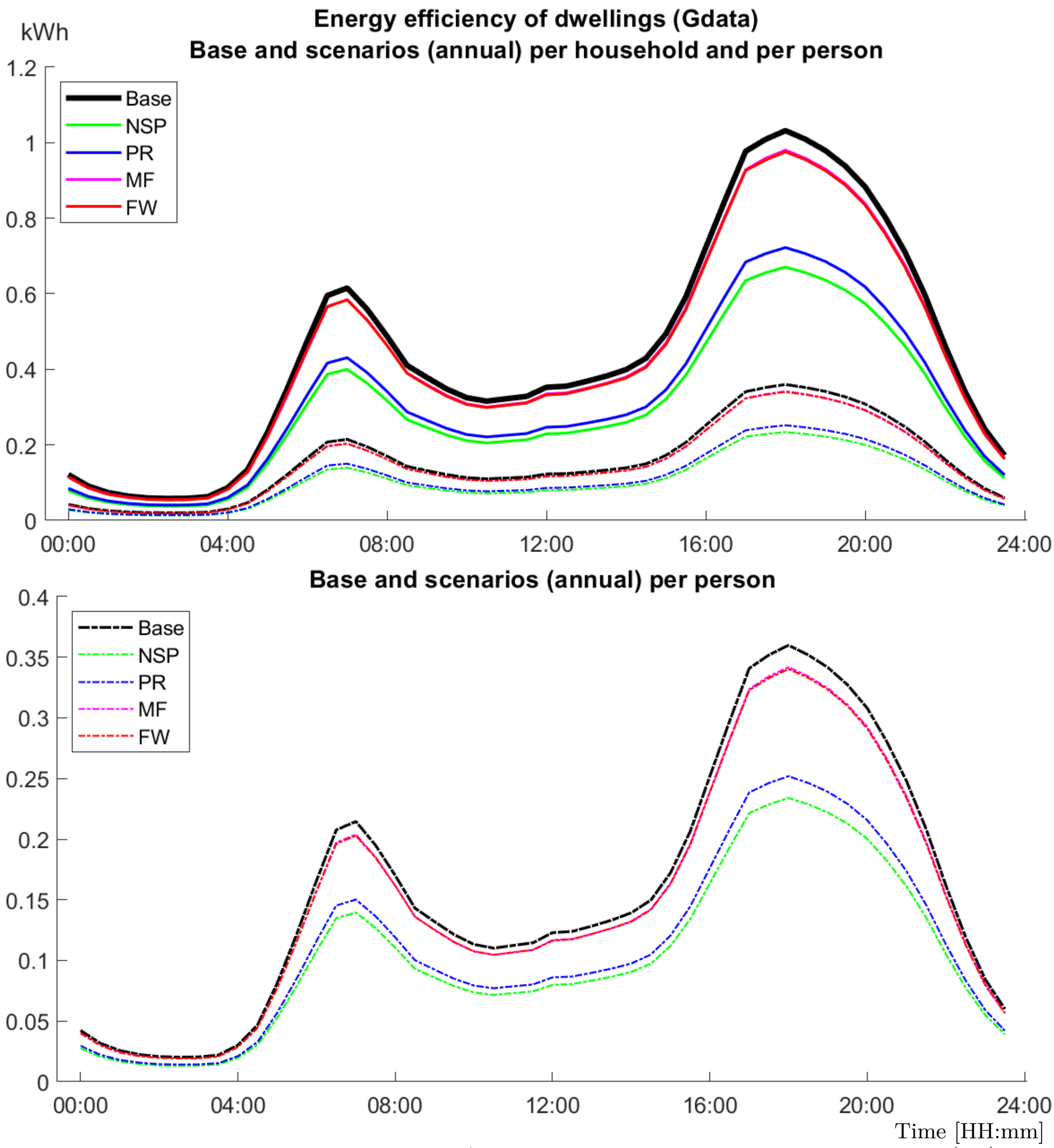


Figure 6.5.4.2: Base and projections of the annual gas demand per household (up) and per person (down) for 'Energy efficiency of dwellings'.

people varies from the characteristics of the indicator and some context extracted from the general description of the scenarios (see the second part of Table 6.5.5.1). Therefore, the variable has been defined as 'Percentage of children (<15) at home'. This percentage affects both, electricity and gas demand. Therefore, both samples (Edata and Gdata) can be projected for this variable.

The distribution of 'Percentage of children in the household' for Edata is shown in Figure 6.5.5.1 (the distribution for Gdata is similar). This percentage is found by dividing the number of children in the dwelling by the total number of occupants (times 100). Based on this distribution, four groups have been defined: households with no children, those with between 0% and 50% (both values not included) of children, those with exactly 50% of children, and those with more than 50% of children. Table 6.5.5.2 shows the ratios of

Table 6.5.5.1: Characteristics of the indicator 'Age distribution' and context extracted from the general description of the scenarios from DRC (Lombardi et al., 2012).

Age distribution				
Measure *Base*	NSP	PR	MF	FW
	⇑	⇑	⇑	⇔ | ⇓
Percentage over 65 *16*	Ageing population.	Ageing population —more older people, percentage-wise.	The population is ageing.	Overall younger —the majority (poor) do not have access to quality health care services that would extend their lives, and may not limit family size.
Context	Less progeny because of environmental convictions, and longer lifespans.	Longer lifespans, similar progeny as currently.	Similar progeny as currently.	Rich: Similar progeny as currently. Poor: shorter lifespan and more progeny.

these groups in Edata and Gdata, these are the base ratios to obtain the projections. This is also shown specifically for the houses conforming the rich (social classes A and B) and the poor (rest of households) blocks in FW because when projections use ratio-weighted sums, the projection of FW is a composition of the projections for FWr and FWp (see Section 6.1).

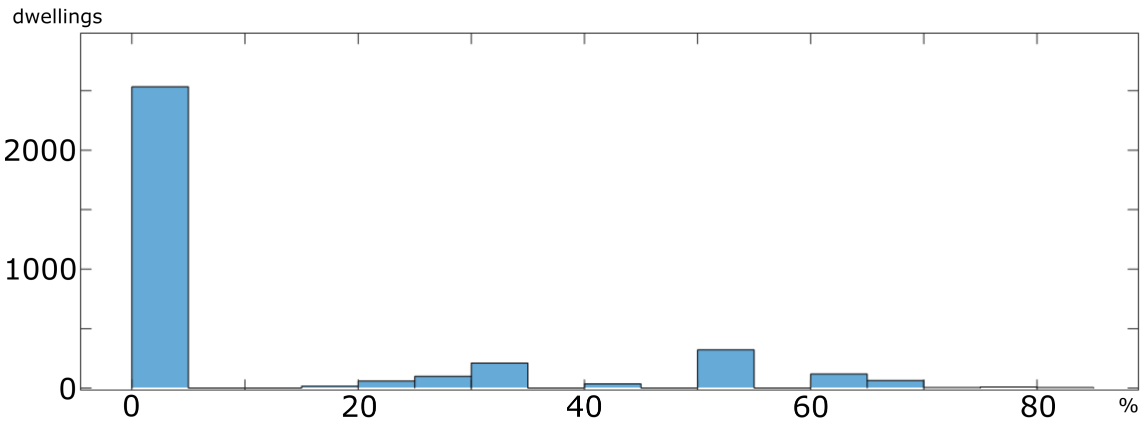


Figure 6.5.5.1: Distribution of percentage of <15 (children) in the household of Edata (number of children divided by total number of occupants).

Table 6.5.5.2: Base ratios for the variable 'Percentage of children in the household'.

	0% children	0 < 50% children	50% children	> 50% children
Edata	0.73	0.12	0.09	0.06
Erich	0.58	0.16	0.18	0.08
Epoor	0.75	0.12	0.08	0.06
Gdata	0.64	0.16	0.13	0.07
Grich	0.54	0.21	0.17	0.08
Gpoor	0.68	0.14	0.12	0.06

Figures 6.5.5.2 and 6.5.5.3 show the electricity and gas demands of each group compared to the total average for all types of day in the samples (the electricity demand of AD is shown in solid lines, that of WD in dotted lines and that of WE in dashed lines). Now, based on the ratios each group has in the samples, and following the characteristics of the indicator and the information about its context, the group ratios for each future scenario can be derived following the process explained in the Box in Page 105. These ratios are shown in Table 6.5.5.3.

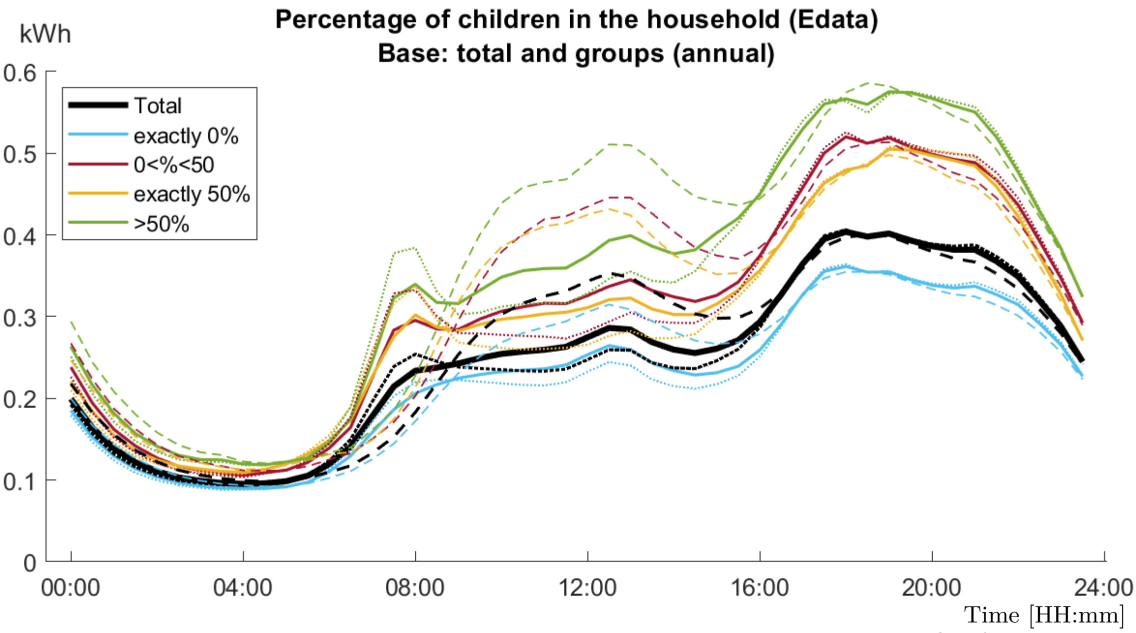


Figure 6.5.5.2: Base daily total and group average electricity demand profile for 'Percentage of children in the household'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

Table 6.5.5.3: Scenarios ratios for 'Percentage of children in the household'.

	Edata				Gdata			
	NSP	PR	MF	FWr|FWp	NSP	PR	MF	FWr|FWp
0% children	0.81	0.78	0.77	0.62|0.38	0.73	0.72	0.70	0.60|0.33
$0 < 50\%$ children	0.14	0.11	0.11	0.15|0.28	0.18	0.14	0.14	0.19|0.29
50% children	0.04	0.07	0.08	0.17|0.20	0.08	0.11	0.12	0.16|0.24
$> 50\%$ children	0.01	0.03	0.04	0.06|0.14	0.01	0.03	0.04	0.05|0.14

With these group ratios, the projections can be obtained using Expression 5.13. The resulting projections for the annual energy demand are shown in Figures 6.5.5.4 (Edata daily profiles) and 6.5.5.5 (Gdata daily profiles), and can be compared with the energy demand of the different groups from Figures 6.5.5.2 (Edata daily profiles) and 6.5.5.3 (Gdata daily profiles). Table 6.5.5.4 shows the resulting daily energy demand averages per household and per person for the scenarios and the groups.

For projections obtained using ratio-weighted sums, the behaviour of the base groups has to be analysed before analysing that of the projections.

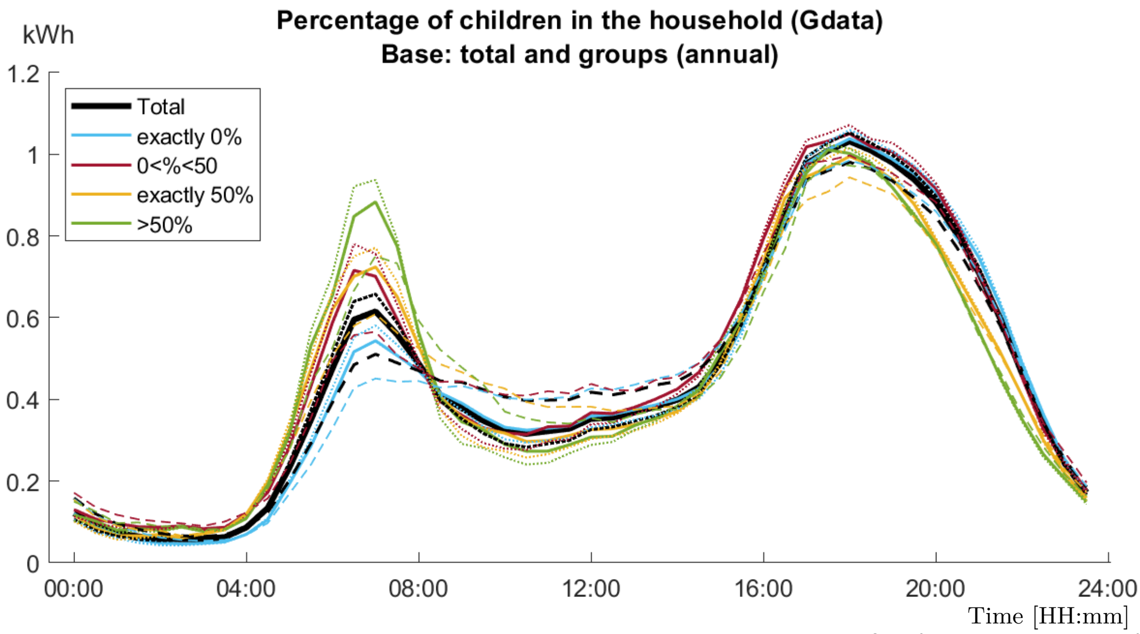


Figure 6.5.5.3: Base daily total and group average gas demand profile for 'Percentage of children in the household'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

Table 6.5.5.4: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Percentage of children in the household'.

Whole year											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4
AD	11.94	11.53	11.53	11.73	13.20	13.61	13.14	10.78	14.75	14.28	16.69
	4.42	4.60	4.54	4.51	3.96	4.36	3.90	5.01	3.69	3.69	3.39
WD	11.73	11.33	11.33	11.53	12.96	13.33	12.90	10.60	14.48	13.98	16.37
	4.34	4.52	4.47	4.43	3.89	4.27	3.83	4.93	3.62	3.61	3.32
WE	12.46	12.03	12.03	12.24	13.82	14.32	13.74	11.22	15.43	15.03	17.50
	4.61	4.80	4.74	4.70	4.15	4.59	4.08	5.21	3.86	3.88	3.55
kWh	Totals Gdata							Groups base Gdata			
AD	21.66	21.67	21.62	21.62	22.07	22.58	21.57	21.38	22.91	21.52	21.70
	7.55	8.12	7.99	7.87	6.71	7.64	6.27	9.57	6.01	5.70	4.43
WD	21.63	21.63	21.58	21.59	22.04	22.50	21.57	21.32	22.92	21.55	21.71
	7.54	8.11	7.98	7.86	6.71	7.61	6.27	9.55	6.01	5.70	4.43
WE	21.74	21.77	21.71	21.71	22.13	22.79	21.57	21.53	22.88	21.44	21.69
	7.58	8.16	8.03	7.91	6.74	7.71	6.27	9.64	6.00	5.67	4.43

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

In this case the percentage of children in the household is strongly linked to the height of the morning peak of gas demand, especially in WD. To the point that, in households consisting of more than 50% children, in WD this peak is almost as high as the evening peak. The effect is smaller but still important in Edata, although for WE it seems to disappear. For electricity, the percentage of children in the household is strongly directly

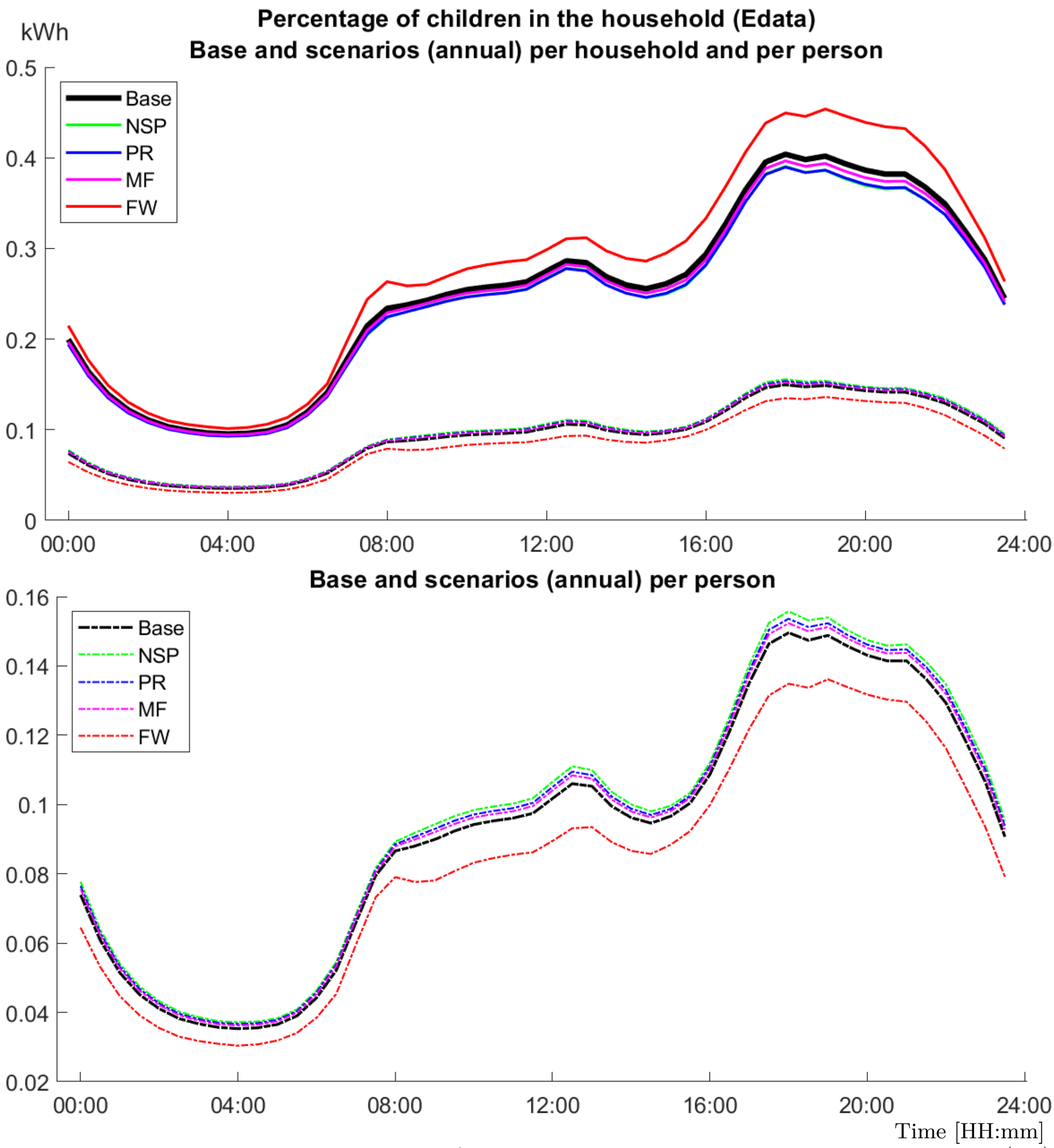


Figure 6.5.5.4: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Percentage of children in the household'.

linked to the average electricity demand during the whole day; the profiles of the different groups are very similar but higher the larger the percentage. Another effect that this percentage has, in this case for gas demand, is to push laterally the profile: households with larger percentage of children tend to start and stop using gas earlier than households without children. Another interesting feature is that this variable has the group with the second lowest gas demand per person (group > 50%), with almost the same average demand as the largest group of 'Household size'. These groups show a very similar energy demand even though they seem to be formed largely by distinct households —they only share 48 households (out of 206 in '>50% children' and 135 in '6+ occupants')—.

The projections for 'Percentage of children in the household' show a clear outlier, FW. The projections of FW indicate a clear increase in electricity demand per household

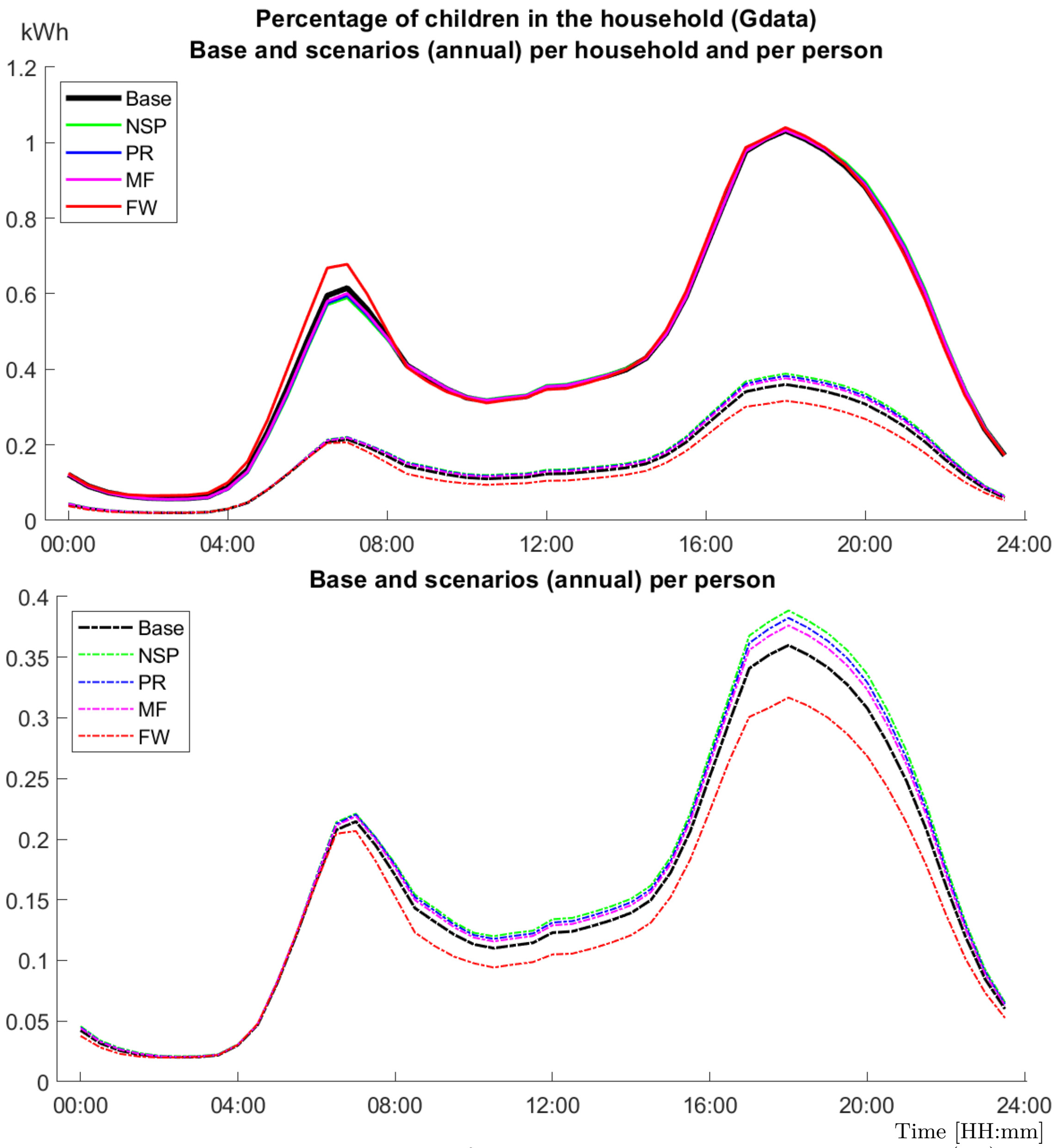


Figure 6.5.5.5: Base and projections of the annual gas demand per household (up) and per person (down) for 'Percentage of children in the household'.

and an equally clear decrease in the electricity demand per person. These effects are also noticeable for gas, but much less marked, although it shows a clear increase in the morning peak of gas demand. This is because in this scenario there is a large increase in households with more children, which tend to demand more gas —especially in the morning— and electricity, Figures 6.5.5.2 and 6.5.5.3. The projections of the other scenarios are very similar to the base scenario. They also show a slight inverse proportionality between the energy demand per household and per person, as with FW. And the "more sustainable" a scenario is (NSP>PR>MF), the more energy demand per person it shows. This is because sustainability is linked to longer life-spans and fewer progeny.

6.5.6 Energy purchasing power

The indicators 'Income' and 'Income Inequality' from DRC (Lombardi et al., 2012), both make reference to economic power of the population, only showing different characteristics of it (roughly the mean and the standard deviation). The income-related information can be projected into each scenario using the two mentioned indicators. However, the influence that income has on the energy demand of households is affected by the energy prices; ultimately, in terms of the capability to consume energy, an increase or decrease in energy price is, effectively, the same as a decrease or an increase in income. Yalcintas and Kaya (2017) show that a decrease in energy use due to a lack of purchasing power can happen in a period with an increase in average income (from now on referred as AI) if the energy price increases enough so that the relation between the two is smaller. And Chang (2015) shows that in a context with countries of diverse economic development, non-high income households increase their energy consumption up to 0.8% for each 1% increase in income, while there is no such increase for high income households. Therefore, what drives household energy demand is the energy purchasing power of the households rather than their income. And so, 'Energy price (domestic)' has to be taken into account together with the indicators related to income.

This variable, thus, is defined as the 'Energy purchasing power' of households. It accounts for both, the changes in the ratios of the social classes (f_i) and the effect that 'income vs. energy price' have towards household energy demand (k_i). In order to define the household groups, and obtain these ratios and corrections, a long analysis of the data in the surveys and that of UK is needed. This analysis has been divided in two sections to make it more understandable and ordered. It is then followed by a third section with the projections obtained.

Trials' data and groupings

First, a general analysis of the survey questions is done, followed by an in depth analysis of Edata. Within this analysis the household groups for the projections of these variables are found. Subsequently, a shorter analysis showing similarities and differences with Gdata is also done. This analysis confirms the conclusions reached for Edata.

The trials' surveys give information about the total income of the household (by direct inquiry) and about the social class of the household (by inquiring about the employment of its chief income earner and its current employment status). For this analysis, it would be ideal to use the information about total household income. However, more than 1/3 or respondents of Edata (1278 out of 3488, 36.6%) and around 1/2 of Gdata (685 out of 1365, 50.2%) refused to answer this question. In addition, the other responses do not seem very reliable. For example, one response corresponding to a household which falls in the social class group DE, the lowest, states that they earn the lowest wages option that the survey provides, *i.e.* 'Less than 15,000 Euros', which seems normal. However, the answer to the periodicity of these earnings states that they are per week —instead of per month, which would seem to fit better their social class. On the other hand, only 1% of respondents refused to answer the question from which the social class of the household is derived (38 out of 3488 in Edata and 20 out of 1365 in Gdata), which asks about the occupation of the chief income earner. This highlights that (1) people may be more likely to openly speak about their employment than about how much they actually earn, and (2) the difficulty to know not only the salary of the chief income earner but also all other salaries, plus whether they are before or after taxes and their periodicity. Therefore, in order to project the effects of the energy purchasing power of the families into the different scenarios, the information about the social class of the household is used.

Social class is a system of demographic classification based on the occupation of the head of the household. In UK the definitions are as follows (ratios of 2016 UK) (Wilmshurst & Mackay, 2010):

Social class A – Upper middle class: higher managerial, administrative or professional (4%).

Social class B – Middle class: intermediate managerial, administrative or professional (23%).

Social class C1 – Lower middle class: supervisory or clerical and junior managerial, administrative or professional (28%).

Social class C2 – Skilled working class: skilled manual workers (20%).

Social class D – Working class: Semi-skilled and unskilled manual workers (15%).

Social class E – Non-working: State pensioners, casual and lowest grade workers, unemployed with state benefits only (10%).

The surveys do not distinguish classes A and B, and D and E. And another class is added, F, for farmers. This is because the surveys were conducted in Ireland, the only country in which farmers have their own class (Ryan, 2013). In 2010 there were 272,020 people working on farms in Ireland (Eurostat, n.d.) while the total number of people employed was 1859100 (996100 men and 863000 women) (Central Statistics Office, n.d.). This means that farmers were 14.6% of all workers in Ireland in 2010. However, they represent only a 2.55% of the respondents of Edata and 0.6% of Gdata. As there is no more information about whether they own the land and farm they work on, they are considered to be skilled working class (C2) for this analysis. An inspection of the electricity they consumed per household and per occupant supports this decision as they do not show significant differences. In addition, the average household size is also very similar, see Table 6.5.6.1.

Therefore, from now on, classes F and C2 are joined to C2F. Table 6.5.6.2 shows the energy demand per household and person, and the average household size of the resulting social class groups.

Table 6.5.6.1: Average daily electricity demand per household, per person and average household size of different social class groups AB, C1, C2, DE and F.

(energy in kWh)	AB	C1	C2	DE	F
Energy per household	5087	4623	4527	3930	4422
Energy per person	1577	1531	1564	1760	1556
Av. household size	3.23	3.02	2.89	2.23	2.84

The values for social classes C2 and F (shadowed) are quite similar.

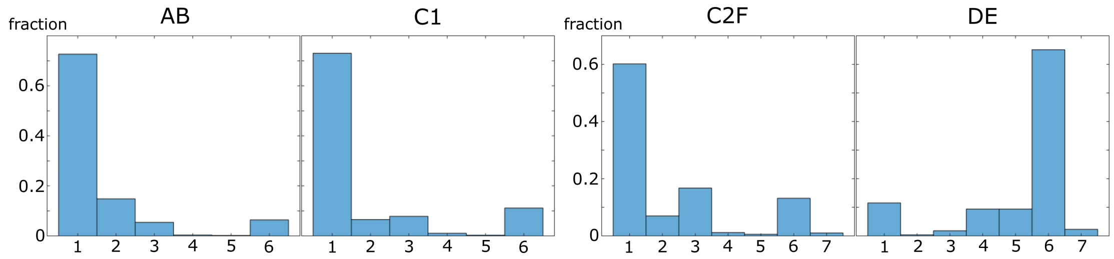
Table 6.5.6.2: Average daily electricity demand per household, per person and average household size for social class groups AB, C1, C2F and DE.

(energy in kWh)	AB	C1	C2F	DE
Energy per household	5087	4623	4513	3930
Energy per person	1577	1531	1563	1760
Av. household size	3.23	3.02	2.89	2.23

Some analysis has to be now done regarding the fact that social classes A and B, and D and E are grouped together. The energy consumption patterns of social classes A and B are expected to be similar, as income is not a factor that usually affects the use of energy in for high income households (Chang, 2015) and their dwelling occupancy patterns are expected to be similar. However, the energy demand patterns of social classes D and E are expected to be quite different. Social class D are workers in badly paid jobs who are expected to need to work many hours to make ends meet (fewer time at home), while social class E are unemployed with the possibility to spend much more time at home. Therefore, it would be useful to separate classes D and E.

In Edata, social class groups AB, C1 and C2F contain around 10% of non-working chief income earners (see Figure 6.5.6.1). In group DE, the amount of non-working chief income earners is, as expected for the reason explained above, larger (although it is of around 90%; which is actually larger than expected since part of it is social class D). In order to attempt to separate E from D in a way similar to that of the other groups (*i.e.* keeping around 10% of E in the non-employed categories), the questions about the household total income were checked. However, the percentage of respondents who refused to answer these questions is even larger in this sub-sample than in the whole sample (almost 50%). Therefore, it is not possible to separate D and E based on the household's total income.

One option now would be to define groups D and E by assigning a percentage of the non-working chief income earners' households of group DE as being members of group D, while the rest would be group E. This way group D could still have around 10% of households with non-working chief income earners. However, the households forming group D would then have to be chosen randomly, without any reasoning behind. Instead, all the households with non-working chief income earners from group DE have been assigned to social class E, while those with working chief income earners have been assigned to social class D. The sizes of these groups are very unequal (∼15% D vs. ∼85% E).



Rubric: (1) An employee, (2) Self-employed (with employees), (3) Self-employed (without employees), (4) Unemployed (actively seeking work), (5) Unemployed (not actively seeking work), (6) Retired, and (7) Carer: looking after a relative family.

Figure 6.5.6.1: Proportion of answers to the question about the employment status of the chief income earner for each social class group.

Now all groups are finally defined. Their average daily energy demands and other information which is later used can be found in Table 6.5.6.3.

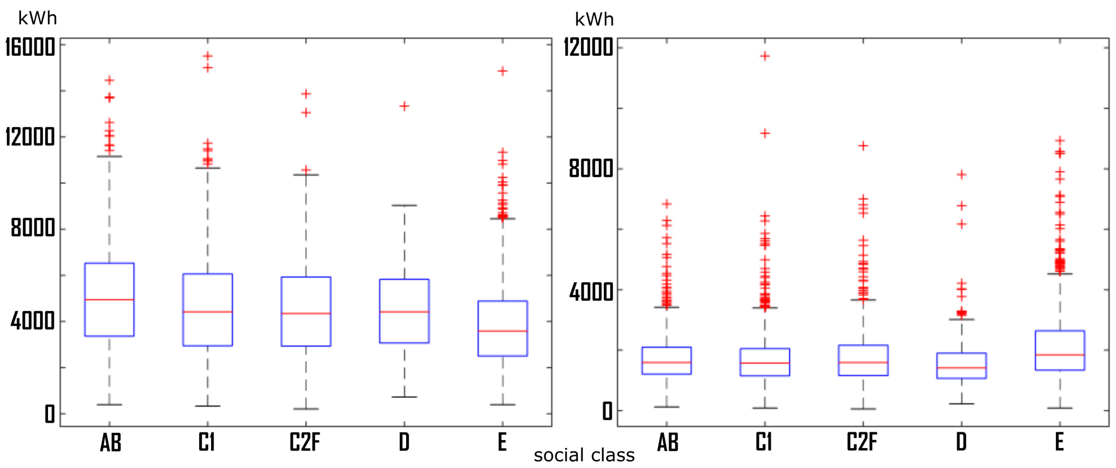
Table 6.5.6.3 suggests, the annual electricity demanded per occupant is considerably higher in social class E, where people tend to be at home for longer time, than in the other social classes. Also, electricity demand is approximately stable within social classes AB, C1 and C2, while in class D it is lower (see Figure 6.5.6.2 as well). This suggests that income is likely to only affect household energy demand for low earner households. Another expected feature is that the median is, in all cases, lower than the average, which corresponds to positively skewed distributions. This happens because the demand for electricity has a hard lower limit (one cannot consume less than 0 kWh), but not an upper limit. One can also see that the ratios of the groups do not correspond to these in the UK; group E is especially overrepresented and groups D and AB under-represented. The use of electric heating is low and fairly constant within groups, therefore it should not have an effect in the comparison of the electricity demand between social classes. Figure 6.5.6.2 shows, with box-plots, the information just described in words.

The box distribution in Figure 6.5.6.2, shows the strong effect that the number of occupants has on the electricity demand per household. Although in the per person plot

Table 6.5.6.3: Data about social class groups AB, C1, C2F, D and E.

(energy in kWh)	AB	C1	C2F	D	E
Energy per household	5087	4623	4513	4550	3831
E. per household median	4947	4413	4343	4415	3582
Energy per person	1577	1531	1563	1436	1838
Av. household size	3.23	3.02	2.89	3.17	2.08
Use of electric heating	4.1%	3.7%	2.7%	5.4%	5.2%
Group ratio Edata	0.15	0.27	0.20	0.05	0.33
Group ratio UK	0.27	0.28	0.20$^{(*)}$	0.15	0.10

Average and median daily electricity demand per household, average daily energy demand per person, average household size, percentage of households using electric heating and group ratio obtained for social groups AB, C1, C2F, D and E of Edata. The ratio of these groups in UK 2016 is shown as comparison as well. $^{(*)}$: the value for UK in 2016 is for social class C2 instead of C2F because in UK there is no social class for farmers.



For each box-plot the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the '+' symbol.

Figure 6.5.6.2: Box-plots: annual electricity consumed per household (left); annual electricity consumed per occupant (right).

groups AB, C1, C2F and D have relatively constant electricity demand and that of group E is larger, in the per household plot there is a clear trend upwards with income power. This suggests that higher income households are larger than lower income households, especially than households in group E —which it is formed by non-workers which presumably stay longer at home—. The larger the household is, the more its members share appliances (*e.g.* TV) and use them at higher capacity (*e.g.* washing machine), therefore reducing their effective electricity demand per person. This effect may hide a correlation between income and electricity demand within the working classes. In order to investigate the influence that household size has on the electricity demand of the different social classes, the average electricity demand of households of different sizes has been plotted for each social class, both per household and per person, see Figures 6.5.6.3. A table has also been generated showing the amount of households of different sizes in each social class group, see Table 6.5.6.4.

Table 6.5.6.4: Number of households of specific size per social class.

Household size	1	2	3	4	5	6+
AB	58	141	90	123	65	35
C1	154	259	167	182	114	54
C2F	103	209	137	130	63	26
D	18	51	39	48	20	8
E	397	481	143	86	28	21

These plots show the strong inverse relation between electricity consumption per person and the amount of occupants in the dwelling. It does not seem to show any relation between income and electricity demand. And, strangely, it does not even show any trend of social class E consuming more electricity than the other social classes (not even within households made of 1 or 2 occupants, where the effect of one person staying longer at

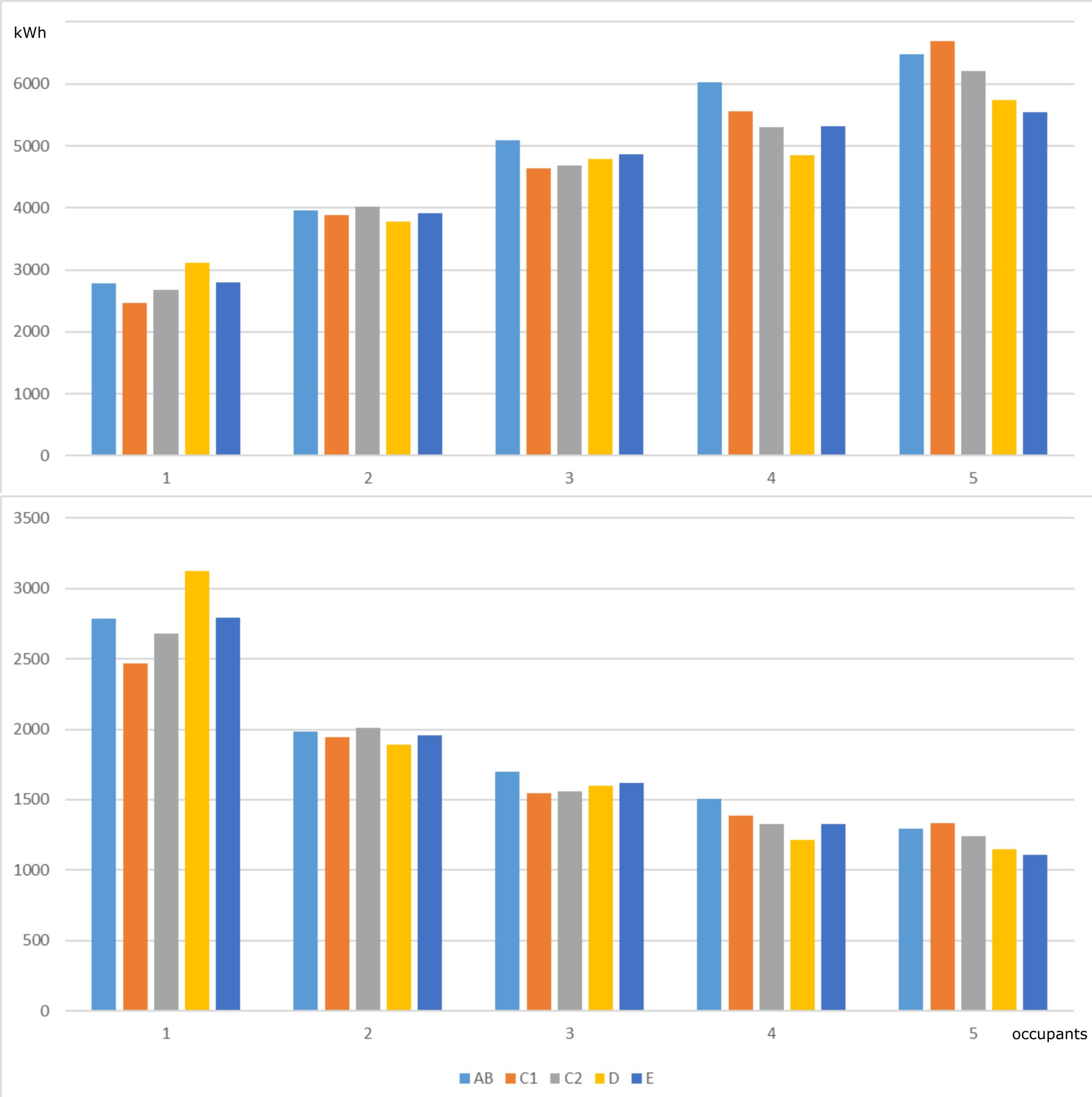


Figure 6.5.6.3: Annual average electricity demand per household and social class in n-occupant-households (top), and per person (bottom).

home would be more apparent). Note that households with more than 5 occupants are not plotted, however, they represent only 21 households out of the 1156 (1.82%) households in group E. The larger amount of electricity consumed per person in social class E seems to be only due to the disproportionate amount of 1 and 2 person households in the group (in smaller households, electricity consumption per person is much higher than in larger households) and the smaller amount of larger households in this social class compared to the other classes. The results for social class D are, in general, much less representative than those of the other social classes due to their small amount of households, especially for households with only one occupant. Note that, although in general there are not many households of 5 or more individuals, the energy demand of these households shows less extreme behaviours as they are the aggregation of the electricity consumed by 5 people.

The general conclusion is that, although it may seem strange, one cannot say that there is any relation between income and electricity demand per person or per household in Edata. Social class E does not show a higher energy demand, not even compared with group D. What is clear is an inverse relation between electricity demand per person and number of occupants in the dwelling. In their concise literature review, Huebner et al. (2016) show that households with higher income tend to be in the higher end of electricity consumption. However, this tendency decreases or even disappears when controlling for other variables, in particular by appliance ownership (Huebner et al., 2016). A similar result is obtained here but controlling for the variable household size.

In a similar analysis for Gdata, one can see that the decision to group farmers (in this case only 8 respondents, 0.6%) with C2 still holds. In addition, the lack of relation between income and gas demand per person or per household persists, see Figures 6.5.6.4.

The main difference in the energy demand trends between the electricity and gas trials is social class D in households of 3 members. However, note that this group in both cases contains very few households, making it much less representative. The other main difference in the trends is social class E in households of 2 members. In this case the amount of households in that group is large for both samples.

Despite these differences, the conclusions from the analysis of Edata hold for Gdata. Therefore, in the samples analysed here there is no apparent relation between income and energy demand per person or per household. In the literature, the case of household energy (electricity and gas) demand is similar to that of electricity alone, explained above. Income tends to be linked to household energy demand in different degrees depending on the study, ranging from almost no link (Dresner & Ekins, 2006) to being strongly linked (Druckman & Jackson, 2008). When income is controlled with other variables this link tends to be weaker, but in general income influences energy use (Guerra-Santin et al., 2009; Huebner, Hamilton, Chalabi, et al., 2015; Kelly, 2011; Steemers & Yun, 2010; Wyatt, 2013).

In this section, the groups to obtain the projections for this variable have been found, and are social classes AB, C1, C2F, D, and E.

UK data and derivation of corrections and ratios

Now that the different social classes from the sample are defined and their energy behaviour analysed, it is time to analyse the data for UK.

As explained above, from the three indicators related to the energy purchasing power of households —'Income', 'Income inequality' and 'Energy price (domestic)'—, the proportion between 'Income' and 'Energy price (domestic)' roughly determines the ability of the household groups to purchase energy, while 'Income inequality' affects the distribution of social classes in each scenario.

Assuming changes in GDP (Gross Domestic Product) per capita to be proportional to these in the AI (average income) (Montana Labor Market Blog, 2016), and taking the data

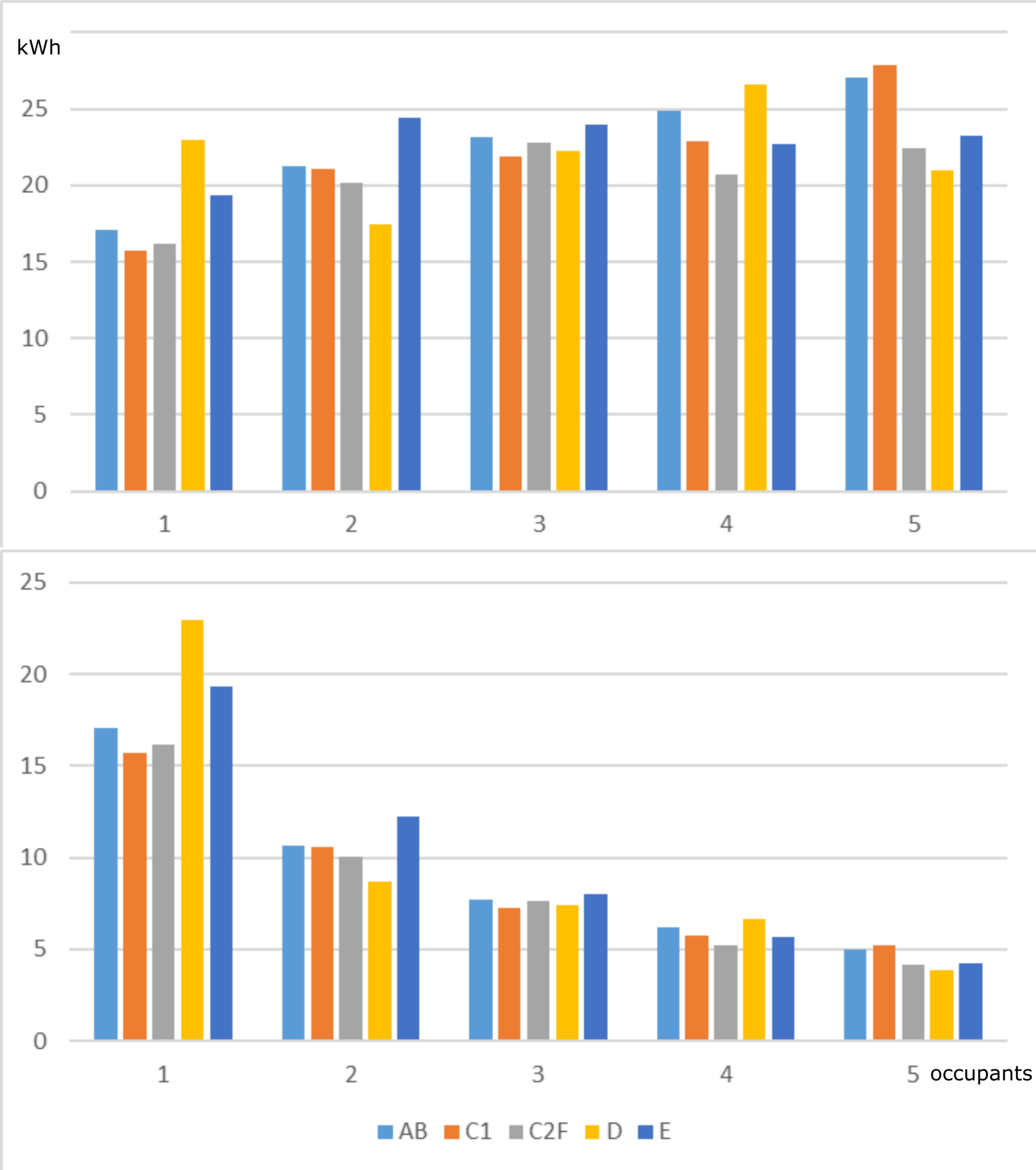


Figure 6.5.6.4: Daily average gas demand per household and social class in n-occupant-households (top), and per person (bottom).

from the UK (HM Revenue and Customs [HMRC], 2012), the AI for the period 2009-2010 in UK can be found (values after tax are used because these reflect the income households can use). This is £21,532, which is very similar to the GDP per capita from the baseline of the indicator 'Income' (£22,700). One can then separate the different social class groups from (HMRC, 2012) taking into account their ratios shown in Table 6.5.6.3 in the previous section —these were (in 2016 UK): AB, 27%; C1, 28%; C2, 20%; D, 15%; E, 10%—. With this, the AI for each social class in 2009 UK can be found (AI_i^{UK}). See Table 6.5.6.5 for these values.

> Note that there are 99 percentiles and the base of a percentage is 100. Therefore, and in order to keep ratio values simple, the social class with the lowest normalised standard deviation (*i.e.* the social class with less income disparity), is shortened one percentage point. This way the addition of all percentages is 99 instead of 100, which then fits the amount of percentiles. This small change does not have a relevant impact in the analysis and keeps everything simpler. The social class with the lowest normalised standard deviation is social class D (see normalised standard deviations in Table 6.5.6.5), which is taken to comprise 14 percentiles although its percentage in 2016 UK is 15%.

Now one would expect that the AI of each social class (AI_i^{UK}) multiplied by their respective ratio and added up would produce the total UK AI found above. Indeed, the difference between these values is only 1% (see Table 6.5.6.5).

Table 6.5.6.5: Social class personal incomes after tax (in £)

Social class	Ratio UK	AI_i^{UK}	Weighted AI_i^{UK}	Normalised SD
E	0.10	7,827	783	0.090
D	0.15 (0.14)	10,471	1,466	0.073
C2	0.20	13,735	2,747	0.089
C1	0.28	19,857	5,560	0.131
AB	0.27	39,856	10,761	0.429
Total	1	*21,532*	21,317	0.693

Social class ratios in 2016 UK, their AIs (AI_i^{UK}), their weighted AIs (AI_i^{UK} times ratio), and normalised standard deviations. In row Total, column AI_i^{UK} is the UK 2009-2010 AI obtained above from (HMRC, 2012), and column Weighted AI_i^{UK} is the sum of the weighted AI_i^{UK} ($\sum AI_i^{UK}$) of each social class above. The difference between these two values is of only ∼1%.

One can see that the differences in income are larger for richer percentiles. Especially in group AB, these differences are very large. This is expected due to the great increase in income in the last percentiles of the distribution and the fact that social classes A and B are grouped together forming a rather large group.

In the next paragraphs, the ratios of the social classes in each future scenario are derived based on the characteristics of 'Income inequality'. Then, the AI of each social class in each scenario (AI_i^{Sc}) is found based on the characteristics of 'Income'. And finally, their energy purchasing power (AI_i^{Sc}/energy price) is calculated for all scenarios with the prices from 'Energy prices (domestic)'. Each group's correction for the projections (k_i) is found based on these energy purchasing powers, but they are not equal to them. Note that the corrections do not have to convey the variations on the energy purchasing power but the effects these variations have on each group's energy demand.

The characteristics of the indicators 'Income inequality' and 'Income' from DRC (Lombardi et al., 2012), and 'Energy prices (domestic)' from its extension (Banchs-Piqué et al., 2020) are shown in Table 6.5.6.6.

Table 6.5.6.6: Characteristics of the indicators 'Income inequality', 'Income' and 'Energy prices (domestic)' from DRC and the extended DRC (Banchs-Piqué et al., 2020; Lombardi et al., 2012).

Measure *Base*	NSP	PR	MF	FW
Income inequality				
	⇓	⇑	⇑	⇓ | ⇓
Gini coefficient *0.34*	Gap between rich and poor decreases.	Despite attempts to balance the objective of high economic growth with strong policies for distributional equity, the gap between rich and poor increases relative to today.	Gap between the poor and the rich increases substantially. The lowest earners (20% of the population) earn <10% of the highest earners (20% of population).	Income inequality increases dramatically driving more people into deep poverty. This scenario has the most inequality overall, although perhaps more equity within each 'class' (rich/poor).
Income				
	⇑	⇑	⇑	⇑ | ⇓
GDP (£)/ capita *£22,700 (2009 baseline)*	GDP per capita increases by 45% to £32,915 (based on Western Europe scenario).	GDP per capita increases 82% to £41,314 (based on Western Europe scenario).	GDP per capita increases 128% to £51,756 per capita per year (based on Western Europe scenario).	GDP per capita increases by 72% to £39,044 (based on Western Europe scenario).
Energy prices (domestic) - Electricity (e) and Gas (g)				
	e⇑ g⇓	e⇔ g⇓	e⇑ g⇑	e⇑ g⇑
p (penny sterling)/ kWh *e: 15.47 p/kWh g: 4.31 p/kWh (2016)*	The electricity price will increase similarly to that in MF (17.36 p/kWh). The gas price will decrease further than that in PR (3,54 p/kWh).	The electricity price will be very similar to the current one, 15,25+ p/kWh. The gas price will steadily decrease until 3,54 p/kWh.	The electricity price will increase almost steadily until 17,36++ p/kWh. The gas price will steadily increase until 6.21 p/kWh.	The electricity price will increase even further than that in MF (17.36+++ p/kWh). The gas price will increase but less than that in MF (6,21– p/kWh).

Based on the characteristics of 'Income inequality' and the ratio of the social classes in UK (the base scenario), and following the process explained in the Box in Page 105, the ratios of each social class are found for each scenario (f_i^{Sc}). The *preliminary* AI for each scenario is then found by adding up the multiplication of the ratios of each social class in the scenario times their AI in UK (AI_i^{UK}). This preliminary AI is referred to as *Social Class distribution AI* (SCdistAI in the tables). Table 6.5.6.7 shows the ratios derived for each social class in each scenario, their corresponding weighted AIs and the resulting scenario *Social Class distribution AIs*.

The origin of these ratios is, however, the base scenario. Afterwards, these ratios will be transformed to make their origin be the group ratios in the data samples. It would also be possible —and simpler— to directly obtain the ratios with origin in the data samples. However, the ratios with origin in the base scenario are needed for the calculation of

Table 6.5.6.7: Scenarios' social class ratios with origin in the base scenario and AIs.

(AIs in £)	AB		C1		C2		D		E		SCdistAI
Base	0.27	10,761	0.28	5560	0.20	2,747	0.15	1,466	0.10	783	21,317
NSP	0.26	10,362	0.49	9730	0.17	2,335	0.05	524	0.03	235	23,186
PR	0.37	14,747	0.29	5759	0.18	2,472	0.11	1,152	0.05	391	24,521
MF	0.40	15,942	0.16	3177	0.11	1,511	0.17	1,780	0.16	1,252	23,663
FW	0.35	13,949	0.01	199	0.03	412	0.26	2,723	0.35	2,739	20,022

For each social class its derived ratio in all scenarios (f_i^{Sc}) —first column— and the resulting weighted AI ($f_i^{Sc} \cdot AI_i^{UK}$) —second column—, and the resulting *Social Class distribution AI* (SCdistAI) for each scenario

scenario AIs, which is the first step to obtain the corrections (k_i) for each social class group.

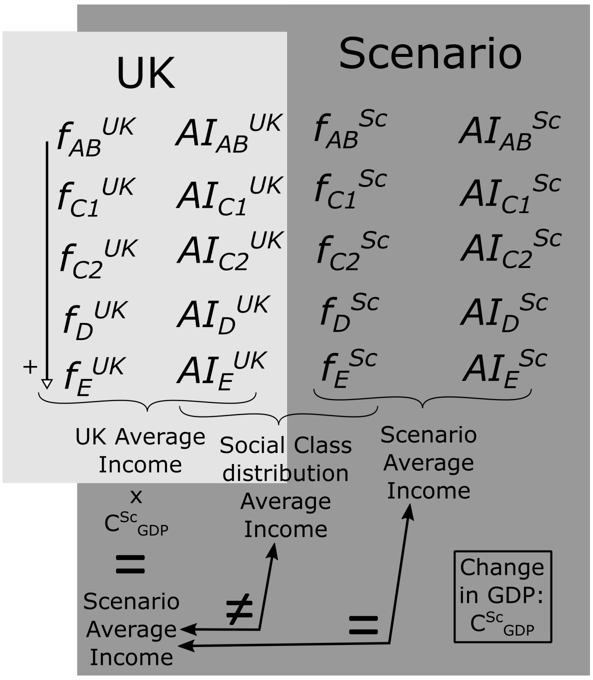
The ratios found account for the changes in 'Income inequality' in each scenario. And, as seen, these have an effect in the total AI ($\sim$GDP per capita) of the scenarios, the total *Social Class distribution AI*. However, the group *Social Class distribution AIs* are still far from the scenario AIs, which are obtained by applying the change in GDP conveyed by the characteristics of the indicator 'Income' to the total AI of UK (row total in Table 6.5.6.5). Table 6.5.6.8 shows the change in GDP per capita in each scenario (which is equal to the change in AI in each scenario), the corresponding scenario AIs (obtained by applying the change in GDP per capita to the AI of UK), the scenario *Social Class distribution AIs* (from Table 6.5.6.7), and the difference between these last two values.

Table 6.5.6.8: Difference between scenario AIs and *Social Class distribution AIs*.

	Change in GDP (from 'Income')	Scenario AI (£)	SCdistAI (£)	Difference (£)
Base	–	21,532	21,317	–
NSP	+ 45%	31,221	23,186	8,036
PR	+ 82%	39,188	24,521	14,668
MF	+ 128%	49,093	23,663	25,430
FW	+ 72%	37,035	20,022	17,013
			18,119	*18,916*

Change in GDP per capita expressed in the indicator 'Income', corresponding scenario AI (UK AI increased by the change in GDP per capita), *Social Class distribution AI* (SCdistAI, from Table 6.5.6.7), and difference between these AIs. Italic values for FW are adjusted values accounting for the loss in economic power of poor social classes in that scenario.

Figure 6.5.6.5 shows graphically the difference between UK AI, *Social Class distribution AI* and scenario AI using the base and scenario ratios, AI_i^{UK} (social class AI in UK), AI_i^{Sc} (social class AI in the scenario) and C_{GDP}^{Sc} (the change in GDP in the scenario): UK AI is obtained by multiplying the social class ratios in UK by the UK social class AIs ($f_i^{UK} \cdot AI_i^{UK}$); the *Social Class distribution AI* of a scenario is obtained by multiplying the social class ratios in the scenario by the UK social class AIs ($f_i^{Sc} \cdot AI_i^{UK}$); and the scenario AI is obtained by multiplying the social class ratios in the scenario by the scenario social class AIs ($f_i^{Sc} \cdot AI_i^{Sc}$) —these AI_i^{Sc} are found in the following paragraphs—, as well as when UK AI is multiplied by the change in GDP in the scenario.



Where f_i^{UK} are the ratios of the groups in UK, AI_i^{UK} are the social class AI in UK from (HMRC, 2012), f_i^{Sc} are the ratios of the groups in the scenario and AI_i^{Sc} the resulting social class AI in the scenario.

Figure 6.5.6.5: Difference between UK, social class distribution and scenario average incomes.

The income of the different social classes does not necessarily increase homogeneously. Following the description of the indicators 'Income' and 'Income inequality', one can say that the relative income increase is roughly homogeneous for all the social classes in NSP and PR —although slightly skewed to the poor and the rich respectively—, and that in MF the income increase of the richer classes is larger than the rest. FW is, however, a totally different case. Although the general income increases, the income of the 65% of poor population decreases (almost half of the poor live in informal settlements). This effect is especially strong within the 'less poor' of the poor social classes (social class C1 and C2). This is because there is an increase of equity within the poor with the incomes tending to converge to those of the poorer classes. Table 6.5.6.9 shows, among others, the decrease rate (and factor) derived for each social class in FWp and their resulting adjusted weighted incomes.

Table 6.5.6.9: Decrease rates and corresponding adjusted AIs for FWp.

	UK AI (£)	Decrease rate (factor)	Adjusted AI (£)	Ratio (f_i^{FW})	Weighted AI (£)	Adj.weig. AI (£)
E	7,827	0.3 (0.7)	5,479	0.35	2,739	1,918
D	10,471	0.3 (0.7)	7,330	0.26	2,723	1,906
C2	13,735	0.4 (0.6)	8,241	0.03	412	247
C1	19,857	0.5 (0.5)	9,929	0.01	199	99

The UK AIs are retrieved from Table 6.5.6.5, adjusted AI means UK AI times factor, weighted AIs retrieved from Table 6.5.6.7), and adjusted weighted AI means weighted AI times factor.

Adding up these adjusted weighted AIs of the poor social classes in FW plus the weighted income of the rich (social class AB), results in a total AI of £18,119 (italic *Social Class distribution AI* values in Table 6.5.6.8). As seen in Table 6.5.6.8, the indicator 'Income' determines the FW AI, which is £37,035. As the AI of the poor groups has already been found, the difference between these two values is the increase in AI of the rich (social class AB). Then, the weighted AI of social class AB in FW is £32,865 (13,949+18,916), and their AI £93,900 (32,865/0.35), which is a factor 2.36 larger than the original shown in Table 6.5.6.7.

Now, to calculate the social classes' increase in AI for the rest of the scenarios, the following expression is used:

$$AI_{AB} \cdot i_{AB} \cdot f_{AB} + ... + I_E \cdot i_E \cdot f_E = T \tag{6.3}$$

Where AI_n is the AI of social class n in the scenario, f_n its ratio, and i_n its increase in AI; and T the scenario AI (given by the characteristics of 'Income'). This equation is indefinite, there are 5 variables (i_n) to solve in one equation. However, from the characteristics of each scenario one can obtain the relative increase of each social class' AI. See them in the Table 6.5.6.10.

Table 6.5.6.10: Relative increases in social class AI for NSP, PR and MF.

	i_{AB}	i_{C1}	i_{C2}	i_D	i_E
NSP	$9.0x_{NSP}$	x_{NSP}	$1.1x_{NSP}$	$1.1x_{NSP}$	$1.2x_{NSP}$
PR	$1.2x_{PR}$	$1.1x_{PR}$	$1.1x_{PR}$	x_{PR}	x_{PR}
MF	$2x_{MF}$	$1.5x_{MF}$	x_{MF}	x_{MF}	x_{MF}

With the relative increases defined for each scenario, Equation 6.3 has a single variable and is, thus, solvable. With the increases found solving the equation, the final social class AI in each scenario can be found. They are shown in Table 6.5.6.11.

Table 6.5.6.11: Scenario AIs and the AIs of their social classes.

(£)	AB		C1		C2		D		E		Scenario
NSP	49,813	12,951	27,576	13,512	20,981	3,567	15,996	800	13,043	391	31,221
PR	66,244	24,510	30,254	8,774	20,927	3,767	14,504	1,595	10,841	542	39,188
MF	94,997	37,999	35,498	5,680	16,369	1,801	12,479	2,122	9,328	1,492	49,093
FW	93,900	32,865	99,29	99	8,241	247	7,330	1,906	5,479	1,918	37,035

AI (first column) and weighted AI (second column) for each social class, and scenario AI.

With these final AIs and the energy prices in each scenario, the energy purchasing power of each group can be easily found, see Table 6.5.6.12. Now, the relation between the energy purchasing power and the energy demand in households has to be found.

In the introduction to this subsection it has been shown that, within non-high incomes, an increase of 1% in income produces an increase of up to 0.8% in energy consumption, while it has no effect within high incomes. As in the data used here there is no sign of

Table 6.5.6.12: Electricity and gas purchasing power for each social class in each scenario.

	e	g	AB		C1		C2		D		E	
	price	price	epp	gpp	epp	gpp	epp	gpp	epp	gpp	epp	gpp
Base	15.47	4.31	2,576	9,247	1,284	4,607	888	3,187	677	2,430	**506**	**1,816**
NSP	17.55	3.50	2,838	14,232	1,571	7,879	1,196	5,995	911	4,570	743	3,727
PR	15.35	3.54	4,316	18,713	1,971	8,546	1,363	5,911	945	4,097	706	3,062
MF	17.55	6.21	5,413	15,297	2,023	5,716	933	2,636	711	2,010	532	1,502
FW	17.65	6.10	5,329	15,393	563	1,628	467	1,351	415	1,202	310	898

Electricity (e) and gas (g) prices in each scenario, followed by electricity purchasing power (epp) and gas purchasing power (gpp) for each social class in each scenario. Cells shaded correspond to energy purchasing power lower than that of social class E in the base scenario (in bold).

any increase or decrease in the energy demand associated with a social class' income, it is assumed that they all belong to high incomes (Ireland is a developed country). It is also assumed that the threshold between rich and non-rich incomes is just below the AI of social class E in the base scenario. Therefore, when the relation between income and energy price (gas or electricity) for a social class in a given scenario is lower than that of social class E in the base scenario (in bold in Table 6.5.6.12), its energy demand is corrected to decrease it (shaded cells in Table 6.5.6.12).

Those groups that struggle to pay for energy are now known and so, their corrections can be calculated. Mirroring the information from (Chang, 2015), each 1% of decrease in energy purchasing power introduces a 0.8% decrease in energy demand. Therefore, the relative decrease in the energy purchasing power with respect to that of social class E in the base scenario has to be found. Then it is multiplied by 0.8 to obtain the percentage of energy demand which has to be subtracted. And finally, as the formalism is such that the corrections are a factor that multiplies the energy demand, it has to be expressed accordingly as a proportion. These corrections can easily be obtained with the following relation: $k_i = 100 - \%\text{E.decrease}/100$. Table 6.5.6.13 shows the corrections found.

Table 6.5.6.13: Corrections arisen from lack of energy purchasing power.

Scenario:	MF	FW	FW	FW	FW	FW	FW	FW
Social class - energy:	E - g	C1 - g	C2 - e	C2 - g	D - e	D - g	E - e	E - g
Epp	1502	1628	467	1351	415	1202	310	898
% decrease in Epp	17.29	10.37	7.72	25.61	17.92	33.83	38.65	50.54
% decrease in energy	13.83	8.30	6.17	20.49	14.33	27.06	30.92	40.43
Correction (k_i)	0.862	0.917	0.938	0.795	0.857	0.729	0.691	0.596

Epp stands for Energy purchasing power. For each 1% decrease in Epp, 0.8% decrease in energy. $k_i = 100 - \%\text{E.decrease}/100$.

Note that in this case FWr and FWp are not explicitly separated. This would not make any sense because FWr and FWp refer to blocks of populations defined by their social class. FWr comprises social class group AB, while FWp comprises the rest of the households, these are those in social class groups C1, C2F, D and E.

Now that the corrections (k_i) have been calculated, the scenario ratios of the groups can be transformed to have as origin the social class group ratios in the data samples rather than those in the UK. To do that, Expressions 5.14 and 5.15 (Page 77) are used. The resulting group ratios and the corrections just found for each scenario are shown in Table 6.5.6.14. These are all the factors needed to produce projections for this variable.

Table 6.5.6.14: Energy purchasing power: social class ratios and corrections.

Group	ratio base	ratio data	NSP		PR		MF		FW	
			f	*k*	*f*	*k*	*f*	*k*	*f*	*k*
Edata										
AB	0.27	0.15	0.16	1	0.24	1	0.21	1	0.13	1
C1	0.28	0.27	0.52	1	0.32	1	0.14	1	0.01	1
C2F	0.20(*)	0.20	0.19	1	0.21	1	0.10	1	0.02	0.94
D	0.15	0.05	0.02	1	0.04	1	0.05	1	0.06	0.86
E	0.10	0.33	0.11	1	0.19	1	0.49	1	0.78	0.69
Gdata										
AB	0.27	0.25	0.24	1	0.35	1	0.36	1	0.28	1
C1	0.28	0.30	0.52	1	0.32	1	0.17	1	0.01	0.92
C2F	0.20(*)	0.20	0.17	1	0.19	1	0.11	1	0.03	0.80
D	0.15	0.04	0.01	1	0.03	1	0.04	1	0.06	0.73
E	0.10	0.21	0.06	1	0.11	1	0.33	0.86	0.63	0.60

(*): the value for the base scenario (UK 2016) is for C2, without farmers.

Groups behaviour and projections

With the corrections and ratios defined, the projections can be obtained using Expression 5.19. The resulting projections for the annual energy demand are shown in Figures 6.5.6.8 (Edata daily profiles) and 6.5.6.9 (Gdata daily profiles). Table 6.5.6.15 shows the resulting daily energy demand averages per household and per person for the scenarios and the groups. However, the behaviour of the base groups has to be analysed before analysing that of the projections to be able to compare them. Figures 6.5.6.6 and 6.5.6.7 show the electricity and gas demand daily profiles of each group compared to the total average daily profile in the base scenario (the samples) for all types of days.

Several differences between social class groups are apparent from the daily average energy profiles and group energy demands: social class group AB tends to use more energy per household, especially more electricity, and do so earlier than the other groups. This group also shows a higher peak in energy demand in the morning which is especially high for gas demand. At the same time, their energy demand per person is quite average. These behaviours fit the result previously found that households of richer social classes tend to be larger, therefore much more likely to contain a higher percentage of children. At the same time, in social class E the morning peak of demand is much later than in the other groups. This also fits perfectly with the fact that in social class E the chief income earner is unemployed and the household size tends to be small (the percentage of unemployed members which do not need to get up early is likely to be very high). This is backed by the fact that for this group this peak starts approximately at the same time for WD and WE, while for the other groups the morning peak in WE tends to converge to

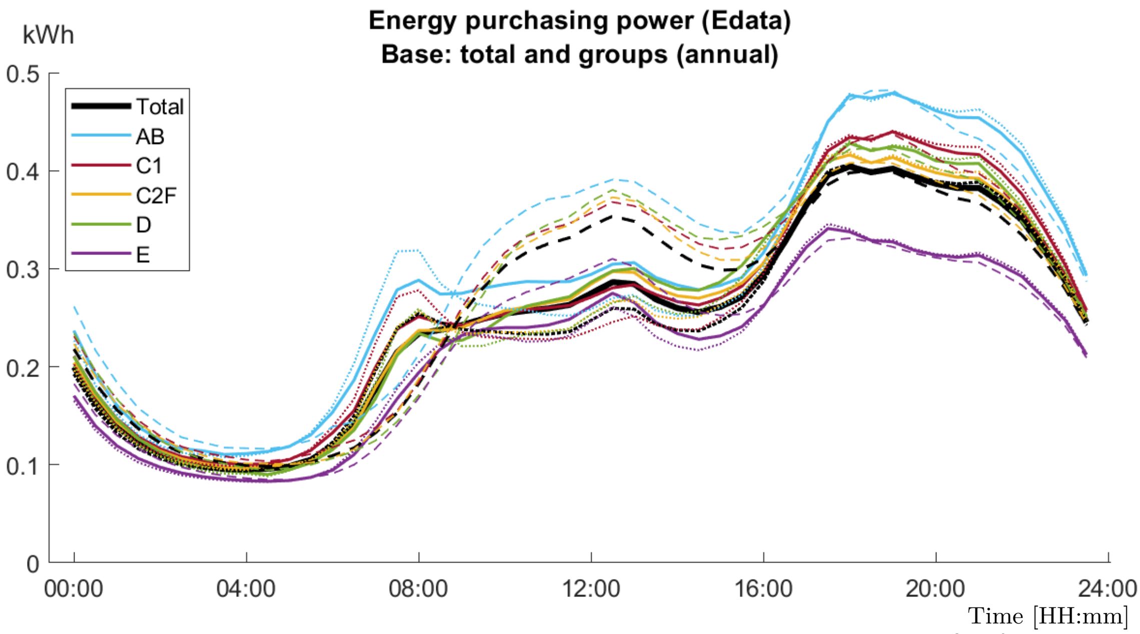


Figure 6.5.6.6: Base daily total and group average electricity demand profile for 'Energy purchasing power'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

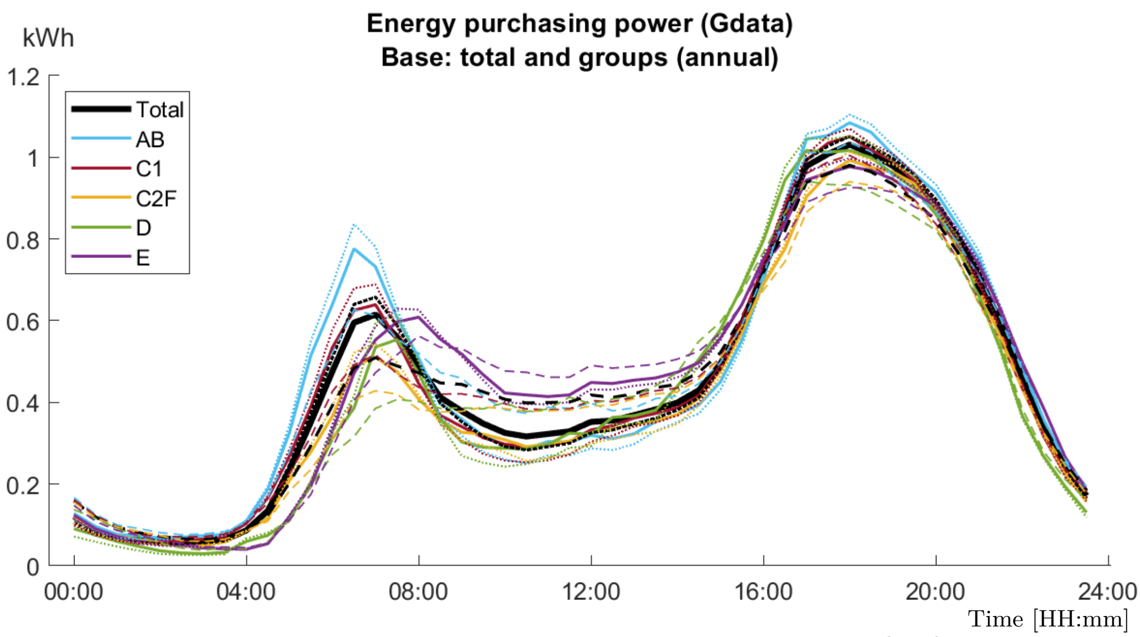


Figure 6.5.6.7: Base daily total and group average gas demand profile for 'Energy purchasing power'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

that of group E. Another clear feature of social class E is that they consume considerably less electricity than the rest while using almost as much gas as class group AB. Their energy demand per person is, by far, the largest. This also fits with the fact that these tend to be smaller households (use less electricity and higher per person demand) but tend to stay more at home during the day (use more gas to heat it during the day). The behaviour of the other social classes is very similar and in between these just described.

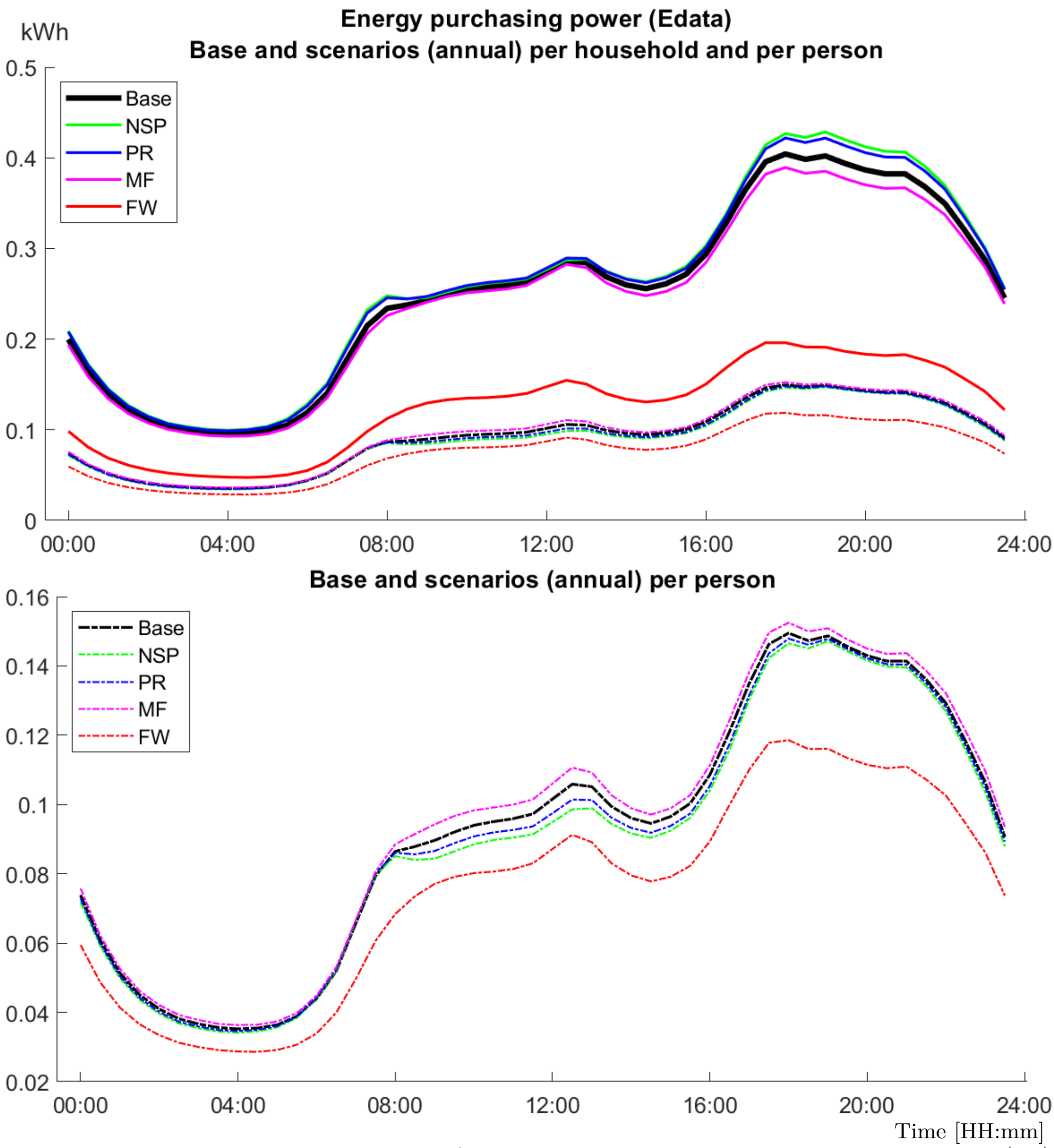


Figure 6.5.6.8: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Energy purchasing power'.

The projections for 'Energy purchasing power' show FW as clear outlier. The projections into FW indicate a clear decrease in energy demand per household and also per person —although the difference relative to the base is smaller—. This effect is mostly due to the lack of energy purchasing power of the poor and exacerbated by the large increase in the ratio of social class E. The effect of the increase in social class E can be seen by comparing the FW's energy demand per household and per person, which are not too far apart. This indicates that, for this variable, the projected average household size in this scenario is small, like in social class E. On top on this effect, a delay in the morning peak can also be observed. However, the large difference in energy demand with respect to the base makes this delay less obvious. In any case, the decrease in energy demand per person is lower than expected. The large amount of FWp population living in informal

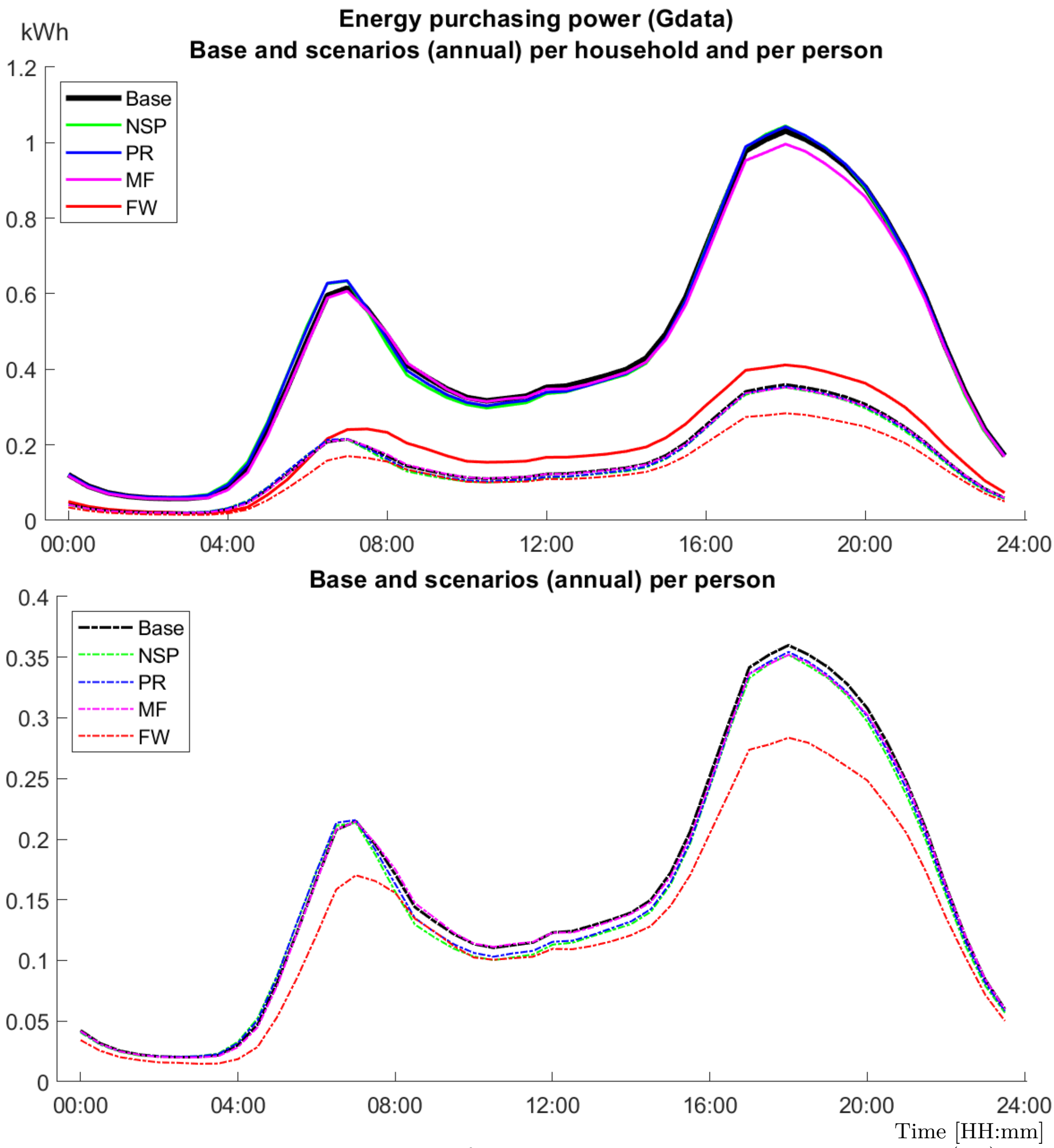


Figure 6.5.6.9: Base and projections of the annual gas demand per household (up) and per person (down) for 'Energy purchasing power'.

settlements would most likely imply a much starker decrease in the energy demand of this scenario. However, as explained in Section 6.1, the energy demand behaviour in informal settlements is uncertain. And, as there is no information about it in the sample, the "worse case scenario" —*i.e.* the case where the energy demand is higher— has been projected.

Leaving FW aside, the differences of the projections into the other future scenarios with the base are much smaller. The main differences are mostly correlated to the ratio of social class E. The more "sustainable" the scenarios are, the less extreme incomes there are, and there are fewer poor. The average household size is fairly constant within social classes, but that of social class E is much lower —and that of social class AB is slightly higher—. The lack of poor in NSP and PR makes them show larger energy demand per household but also smaller per person. The case of MF is also interesting: MF has the

Table 6.5.6.15: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Energy purchasing power'.

Whole year												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	11.94	12.45	12.36	11.58	5.95	1.79	6.58	13.78	12.57	12.24	12.38	10.37
	4.41	4.28	4.33	4.53	3.58	4.31	3.47	4.31	4.18	4.25	3.95	5.00
WD	11.73	12.21	12.13	11.39	5.88	1.75	6.50	13.49	12.30	12.01	12.12	10.26
	4.34	4.19	4.25	4.46	3.53	4.22	3.43	4.22	4.09	4.17	3.87	4.95
WE	12.46	13.07	12.95	12.05	6.14	1.88	6.78	14.49	13.23	12.82	13.03	10.65
	4.61	4.49	4.54	4.72	3.70	4.53	3.58	4.53	4.40	4.45	4.16	5.13
kWh	Totals Gdata							Groups base Gdata				
AD	21.66	21.60	21.70	21.18	9.10	6.33	10.04	22.61	21.54	20.11	20.37	22.39
	7.56	7.28	7.38	7.49	6.21	7.34	5.69	7.34	7.18	6.86	6.74	9.63
WD	21.63	21.54	21.65	21.16	9.12	6.31	10.07	22.54	21.49	20.01	20.37	22.48
	7.55	7.26	7.36	7.48	6.21	7.32	5.70	7.32	7.16	6.83	6.74	9.66
WE	21.75	21.74	21.83	21.24	9.06	6.38	9.97	22.79	21.68	20.36	20.37	22.18
	7.59	7.33	7.42	7.50	6.19	7.40	5.65	7.40	7.23	6.95	6.74	9.54

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

lowest energy demand per household and largest per person and, at the same time, its morning peak is the second latest after FW. This suggests that, although MF is a very rich scenario, social class E considerably affects its energy demand profile.

6.5.7 Space heating

The relevant indicator from the extended DRC (Banchs-Piqué et al., 2020) is 'Use of electric space (and water) heating'; its characteristics are presented in Table 6.5.7.1. In the development of this indicator it was assumed that heating systems are mainly either electric or gas (as is mainly the case in the UK). It refers to both space and water heating and, in some future scenarios, both systems are slightly untangled —they evolve in different ways—. And, although the indicator is focussed on electric vs gas heating systems, using Table 4.5.0.1 the behaviour of other heating systems could also be derived. Therefore, it could be possible to group not only households using electric and gas heating systems but also those using other types of heating systems, and to obtain a projection for space heating and another one for water heating. In order to decide the groupings and projections, Edata and Gdata have to be first analysed.

Edata contains a large number of households using space heating systems of types other than electric or gas (oil, solid fuel, renewables and 'other') and only a small percentage of the total (6.1%) use electricity for space heating at all. The use of this range of heating systems is quite mixed as well, see Table 6.5.7.2. As explained in Section 6.2.1, households with NightSaver tariffs were excluded from the trial, which made electric heating under-represented in the sample.

Table 6.5.7.1: Characteristics and review and context information of the indicator 'Use of electric space (and water) heating' from the extended DRC (Banchs-Piqué et al., 2020).

Use of electric space (and water) heating				
Measure *Base*	NSP	PR	MF	FW
% of households using electric heating *8.5% (2015) (gas: >80%; other: ∼10%)*	⇑ There is a moderate increase in use of electric space heating.	⇑ There is an important growth in the use of electric space heating, mainly incentivised by the government. Probably the increase is slightly smaller in electric water heating as technologies as solar thermal are normally not used for space heating.	⇑ There is a slow increase in the use of electric space and water heating systems.	⇑ | ⇓ The general trend is a slight decrease in the use of electric space and water heating systems. However, it increases within the rich.
Review and context	Although there is a stronger decrease in GHGs produced by household heating than in PR (and electricity is clean), the uptake of electric space and water heating is lower here. The reason is that there is a much greater increase of district heating and other forms of dwelling heating technologies that use the Sun's and the Earth's heat.	Although gas is cheap, as the government is leading a transition to clean energy sources, it incentivises district heating when feasible (often geothermal) and electric heating otherwise –which is the option preferred by the population. The combination of microgeneration and electric heating is particularly appealing for customers. Other heating technologies such as solar thermal also have their role in order to replace gas for heating (mostly water).	Proportionally, the increase in gas price is much higher than that of electricity. This will increase the installation of heat pumps in new buildings and when systems need to be changed. Those who have on-site energy generation will also prefer electric heating.	Rich: similar to MF but probably slightly larger, as nuclear energy seems to be preferred over other sources of energy such as gas. Poor: they are mostly energy poor; therefore, this decreases their use of electric heating. They mostly use biomass or coal for heat.

In terms of heating systems, what influences the electricity demand of households is whether or not they use electric heating systems. Therefore, two groups have to be defined; the households using electric heating systems, and households not using electric heating systems. In order to obtain projections, these groups have to be non-overlapping, the same household cannot be in more than one group. However, most of the households

Table 6.5.7.2: Number of households using each heating system and amount of heating systems used per heating system.

	electric central	electric plug-in	gas	oil	solid fuel	renewables	other
Total users	147	121	1080	2072	930	19	23
Only this one	39%	12%	87%	66%	27%	38%	35%
2 systems	44%	69%	12%	32%	69%	42%	61%
3 systems	15%	17%	1%	2%	4%	11%	4%
4 systems	2%	2%	0.2%	0.2%	0.2%	11%	0%

using electric heating systems use other types of heating systems as well. Therefore, the "electric heating" group has been defined to group the households which only use electric heating (central or plug-in). These are only 72 households, 1.6% of the whole sample.

Due to the small sample of households comprising the 'only electric' heating group and the fact that the construction of the indicator assumes that heating systems are mainly either electric or gas, the "non-electric heating" group has been defined to group only households which use gas heating systems and do not use electric heating (regardless of whether they use other types of heating as well and ignoring those households which do not use gas at all). This group is comprised of 1031 households. This definition of the groups has the advantage that they follow the assumptions taken in the development of the indicator and that their ratios are similar to those of the base scenario (base scenario, 0.09:0.91; Edata groups, 0.07:0.93 —see Table 6.5.7.3, where the ratios in each scenario are derived—).

The difference in electricity demand between these groups is, however, surprisingly small. See Figures 6.5.7.1, they show the electricity demand in winter (top) —when the energy used for space heating is largest— and, keeping the same axes sizes, also in summer (bottom). The group difference was expected to be much larger in winter since the energy used for space heating is the largest contributor to household energy demand by far in UK. It contributes to around 60% of UK's total household energy demand (Palmer & Cooper, 2013), and Irish temperatures are similar to those in UK. In addition, the difference in the electricity consumed by the group which does not use electric heating in winter and summer was expected to be lower as well. The electricity used in winter is far greater than that used in summer, especially in the evening peak, as in summer the peak is almost non-existent while it is very large in winter. This suggests that also in this group there might be a significant use of electricity for some kind of heating purposes.

The indicator 'Use of electric space (and water) heating' refers to both space and water heating systems. These systems are, in some scenarios, slightly untangled (see the characteristics of the indicator in Table 6.5.7.1). The water heating systems from the households in Edata are also mixed and, in addition to the mixing, one of the questions asking about the water heating system refers to the central heating system, which is not defined anywhere and, thus, could be electric or any of the other heating systems. Therefore, due to 1) the only slight detachment of space and water heating systems in the

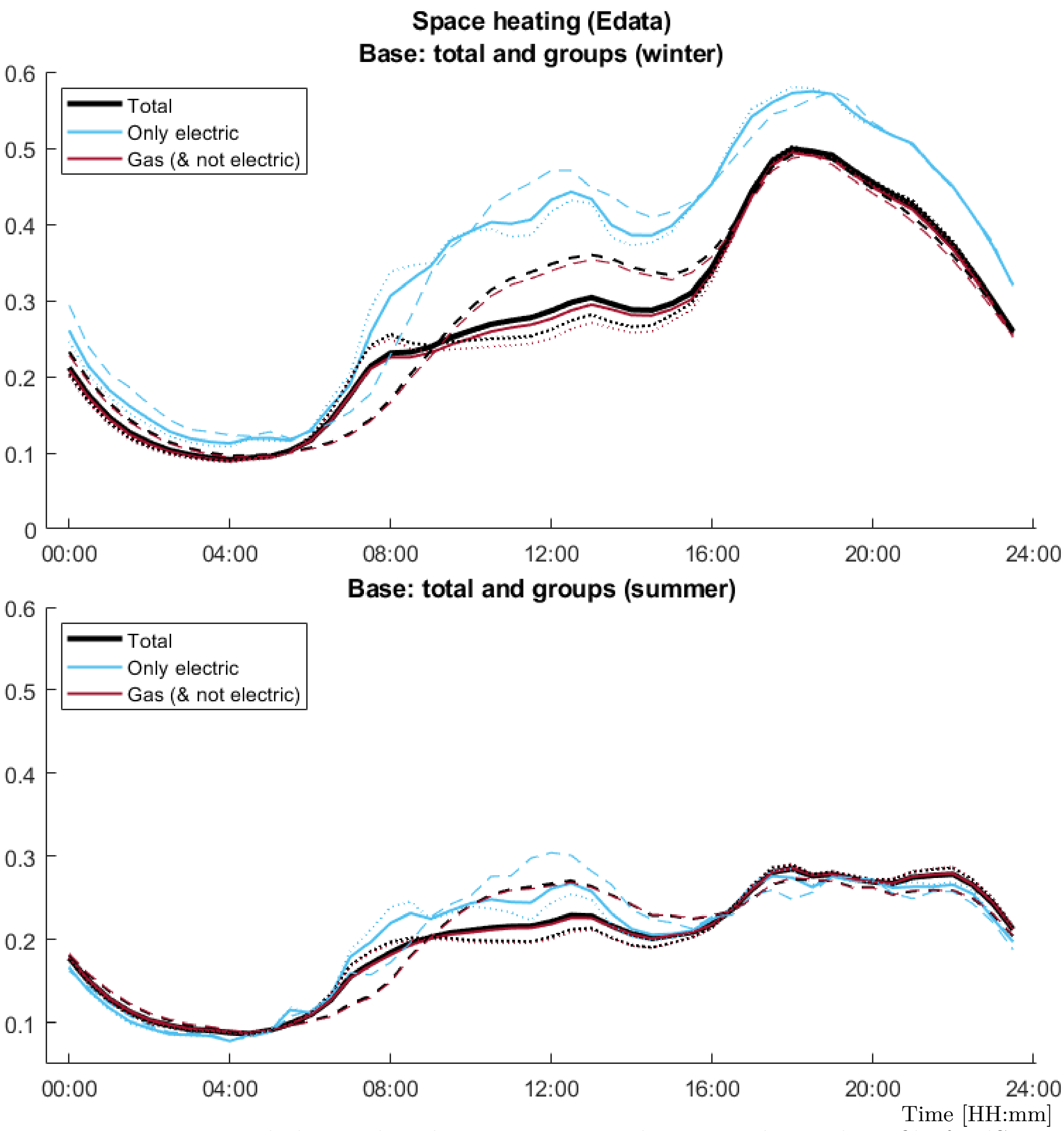


Figure 6.5.7.1: Base daily total and group average electricity demand profile for 'Space heating' in winter (top) and summer (bottom). Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

characteristics of the indicators and 2) the lack of clarity in the types of heating systems used by the households, it was decided to define a single variable, 'Space heating', to project the effects of heating systems. And so, the groups for Edata have been previously defined, 'Only electric' and 'Gas and non-electric' heating.

For Gdata, as expected, the vast majority of households use gas for space heating (only 21 of 1296 participants, 1.6%, do not use gas for space heating). As dwellings are connected to the gas infrastructure mainly to provide heating, the increase or decrease in the ratio of households using gas heating systems directly translates in an increase or decrease of the household population using gas. Therefore, the projection for Gdata is a correction factor affecting the population of households using gas in each scenario.

The group ratios (with origin in the base scenario) in the different future scenarios obtained following their characteristics are shown in Table 6.5.7.3. These are necessary to calculate the changes in household population using gas for the projections of Gdata. And Table 6.5.7.4 shows the group ratios for the future scenarios with origin in Edata. All these group ratios in the future scenarios have been derived following the characteristics of the indicator (with origin in the base scenario and Edata respectively) and following the process explained in the Box in Page 105.

Table 6.5.7.3: Future scenarios' group ratios with origin in the base scenario.

	Base scenario	NSP	PR	MF	FWr|FWp
Electricity	0.09	0.33	0.42	0.25	0.28|0.05
Gas	0.81	0.04	0.15	0.70	0.64|0.05
Other	0.10	0.63	0.43	0.05	0.08|0.90

Table 6.5.7.4: Future scenarios' group ratios with origin in Edata.

	Edata (rich|poor)	NSP	PR	MF	FWr|FWp
Electricity	0.07 (0.04|0.07)	0.29	0.47	0.22	0.15|0.04
Other	0.93 (0.96|0.93)	0.71	0.53	0.78	0.85|0.96

For Gdata, the relation between the ratio of the group 'Gas' in the base scenario and those of group 'Gas' in each future scenario with origin in the base scenario (those in Table 6.5.7.3), correspond to the increase/decrease of the household population using gas. These changes in the household population which use gas, F^{Sc}, are shown in Table 6.5.7.5. They can be applied to other Gdata projections on top of the change of housing population found in Section 6.5.1 to find the total gas demand projected for each scenario.

Table 6.5.7.5: Changes in household population using gas.

	Base	NSP	PR	MF	FWr|FWp
Ratio	0.81	0.04	0.15	0.70	0.64|0.05
F^{Sc}	–	0.05	0.19	0.86	0.79|0.06

With the group ratios found for Edata, their projections can be obtained using Expression 5.13. The resulting projections for the annual energy demand are shown in Figures 6.5.7.2, and can be compared with the energy demand of the different groups in winter and summer from Figures 6.5.7.1. Table 6.5.7.6 shows the resulting daily energy demand averages per household for the scenarios and the groups.

The behaviour of the base groups of Edata has been already briefly analysed above. Besides the small difference in electricity demand between the groups and the large difference between summer and winter of the non-electric heating group, there is not much more to analyse. The curves for the electric heating group are less smooth, probably because of the smaller size of the group. Besides the effects mentioned above, the curves for both groups are mostly parallel and show the typical differences for types of day: WD peak in

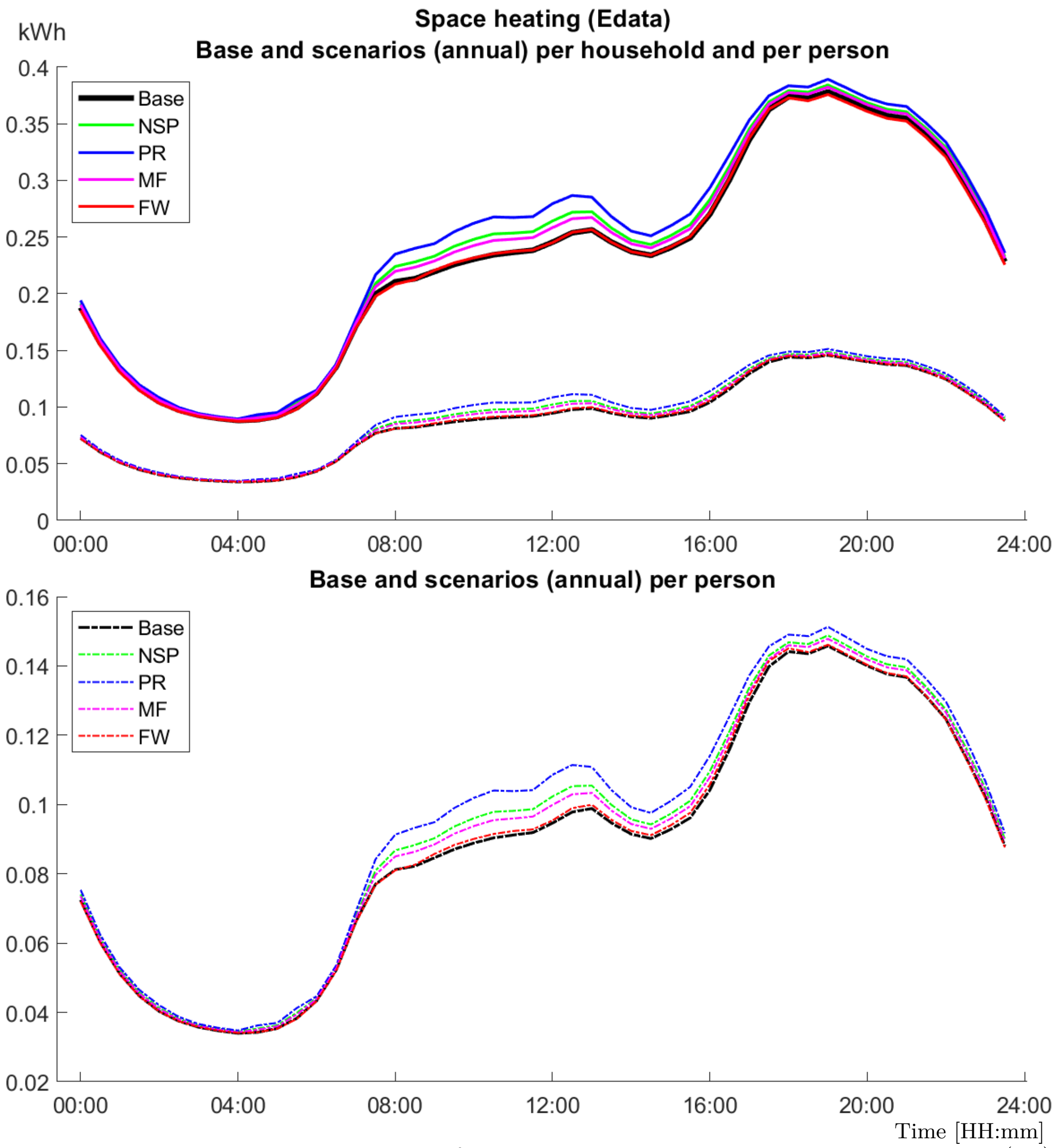


Figure 6.5.7.2: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Space heating'.

the morning, while later wake up in WE which instead of showing a morning peak shows a higher and more constant use of electricity during the day.

Due to the small difference in the electricity demand of the groups, the projections for 'Space heating' do not show large differences between scenarios. As heating is the largest slice of the household energy demand (Palmer & Cooper, 2013), it was expected that these projections would be those showing the largest disparity between the electricity demand of the scenarios, but this is not the case. Following the group ratios, PR is the scenario which shows the largest electricity demand followed by NSP and MF. FW shows an electricity demand very similar to that of the base scenario, slightly lower per household and slightly higher per person. Although at first glance it may seem strange that the "sustainable scenarios" show an increase in electricity demand, this is due to the fact that, as they

Table 6.5.7.6: Base, projections and group's annual daily average electricity demands for the variable 'Space heating'.

Whole year									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	11.02	11.41	11.72	11.29	10.98	12.83	10.71	12.63	10.91
	4.25	4.42	4.55	4.36	4.27	4.23	4.28	4.96	4.20
WD	10.87	11.27	11.59	11.14	10.83	12.65	10.56	12.55	10.75
	4.19	4.36	4.51	4.31	4.21	4.17	4.22	4.93	4.14
WE	11.42	11.75	12.02	11.65	11.38	13.29	11.09	12.82	11.32
	4.40	4.55	4.67	4.50	4.42	4.38	4.43	5.03	4.36

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

produce clean electricity, these scenarios tend to electrify energy consumption. As NSP goes further in the use of community heating systems, their increase in electric heating is lower than that in PR.

6.5.8 Type of building

The relevant indicator from the extended DRC (Banchs-Piqué et al., 2020) is 'Type of building', see its characteristics in Table 6.5.8.1. It conveys, qualitatively, the trends relative to the base scenario of each type of building in the future scenarios. To derive the percentage of each type of building in the different scenarios, one has to take into account that in the UK more than two-thirds of the 2050 housing stock was already built in 2005 (Boardman et al., 2005). These "more than two-thirds" is taken as an average; in each scenario the total amount of buildings varies with the reuse and adaptation of current stock, and with the amount of dwellings built. The metadata contains information of the type of building each family lives in. This information is available for almost all households, only 7 of 3488, 0.20%, in Edata and 1 of 1365, 0.07%, in Gdata miss this information. Although one of the types of building the metadata distinguishes is bungalows, this type of building does not appear in the characteristics of the indicator and has been considered detached houses. Therefore, the variable 'Type of building' defines the following groups: 'Flats'[5], 'Semi-detached houses', 'Detached houses' and 'Terraced houses'.

With the narratives above and the ratios of each type of building in the data sets, one can derive the ratios for each scenario except FW. In FW around one third of the population (nearly half of the poor population —47%—) live in informal settlements. In principle, this breaks the projections method as the data do not contain information on the energy demand in the kinds of "dwellings" from informal settlements. However, as explained in Section 6.1, the ratios for FW are derived as if all FWp live in formal

[5]In the metadata the term apartment is used instead of flat, but the type of building is the same and flat has been chosen as group name.

Table 6.5.8.1: Characteristics of the indicator 'Type of building' from the extended DRC (Banchs-Piqué et al., 2020).

Age distribution				
Measure *Base*	NSP	PR	MF	FW
% of the building stock compared to baseline *Terraced 29.2% Semi-detached 27.6% Detached 22.6% Flat 20.6% (2013)*	Flats: increase. Terraced: similar with tendency to decrease. (Semi-) detached: decrease.	Flats: increase. Terraced: slight increase. (Semi-) detached: decrease (in particular semi-detached, as people who can afford it prefer to pay more (detached) for increased privacy).	Flats: increase. Terraced: moderate decrease. (Semi-) detached: increase.	Rich: Flats: strong decrease. Terraced: slight increase. (Semi-) detached: strong increase. Poor: Flats: stay the same percentage. Terraced: decrease. (Semi-) detached: strong decrease. Appearance of large informal developments with shacks and tend-like dwellings.

settlements, and so, the energy demand projections for FW have to be taken as an upper limit.

Now, based on the ratios of each type of building in the samples (see Table 6.5.8.2), and following the characteristics of the indicator, the ratios for each future scenario can be derived following the process explained in the Box in Page 105. The scenario ratios derived from the characteristics of indicator 'Type of building' are shown in Table 6.5.8.2.

Table 6.5.8.2: Group ratios in Edata and Gdata for the future scenarios.

	Data all	Data rich	Data poor	NSP	PR	MF	FWr|FWp (informal: 0.47)
Edata							
Flat	0.02	0.02	0.02	0.17	0.16	0.04	0.01|0.06
Semi-detached	0.30	0.33	0.30	0.24	0.21	0.32	0.35|0.14
Detached	0.54	0.56	0.53	0.46	0.46	0.56	0.60|0.22
Terraced	0.14	0.09	0.15	0.13	0.17	0.08	0.04|0.11
Gdata							
Flat	0.02	0.02	0.02	0.18	0.17	0.05	0.01|0.06
Semi-detached	0.55	0.55	0.55	0.46	0.42	0.58	0.59|0.24
Detached	0.21	0.24	0.21	0.16	0.17	0.25	0.31|0.08
Terraced	0.21	0.18	0.22	0.20	0.24	0.14	0.09|0.15

With these group ratios, the projections can be obtained using Expression 5.13. The resulting projections for the annual energy demand are shown in Figures 6.5.8.3 (Edata) and 6.5.8.4 (Gdata), and can be compared with the energy demand of the different groups from Figures 6.5.8.1 and (Edata) and 6.5.8.2 (Gdata). Table 6.5.8.3 shows the resulting daily energy demand averages per household for the scenarios and the groups.

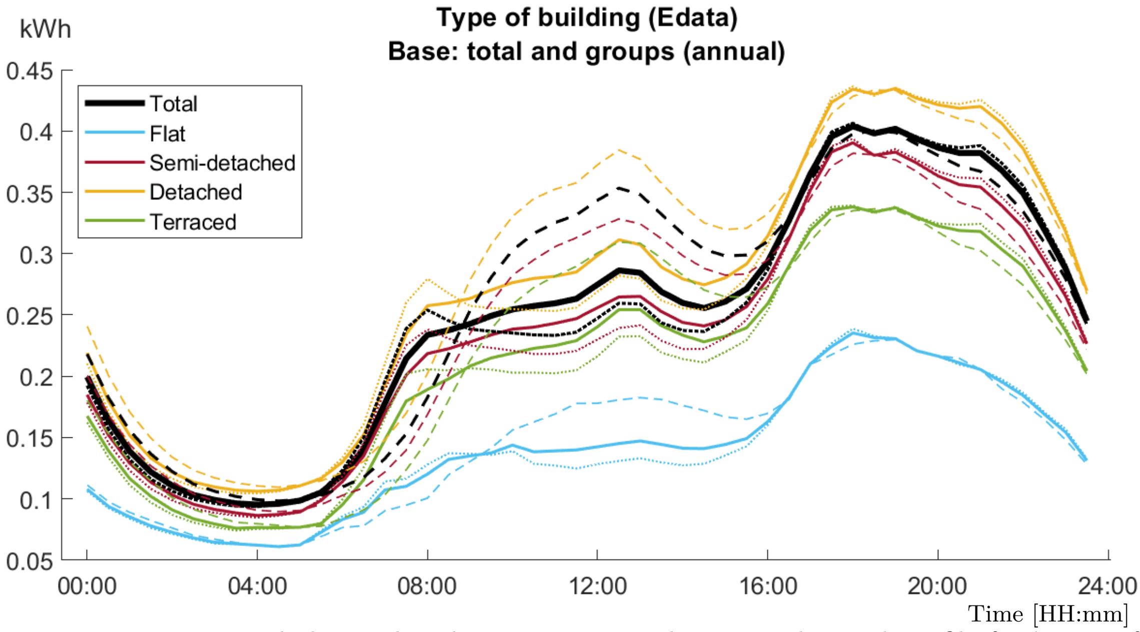


Figure 6.5.8.1: Base daily total and group average electricity demand profile for 'Type of building'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

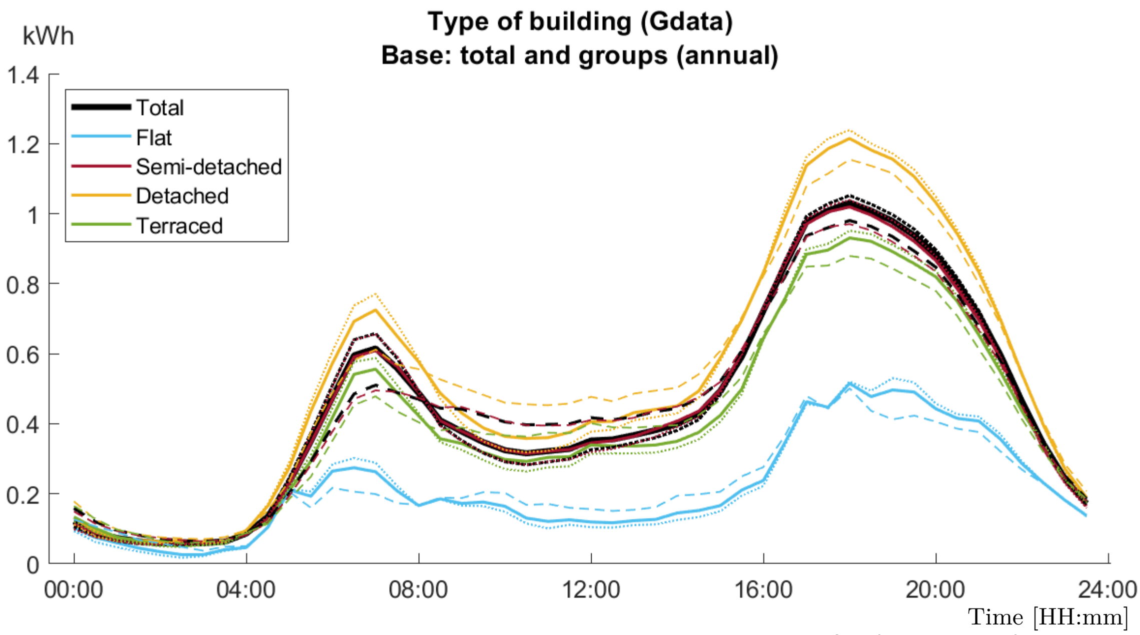


Figure 6.5.8.2: Base daily total and group average gas demand profile for 'Type of building'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

For projections obtained using ratio-weighted sums, the behaviour of the base groups has to be analysed before analysing that of the projections.

In this case the expected behaviour is seen: there is a clear distinction in the energy demand of the different types of buildings with a gradient from compact (flats) to "loose" (detached) dwellings, illustrated by almost parallel lines. The energy demand per house-

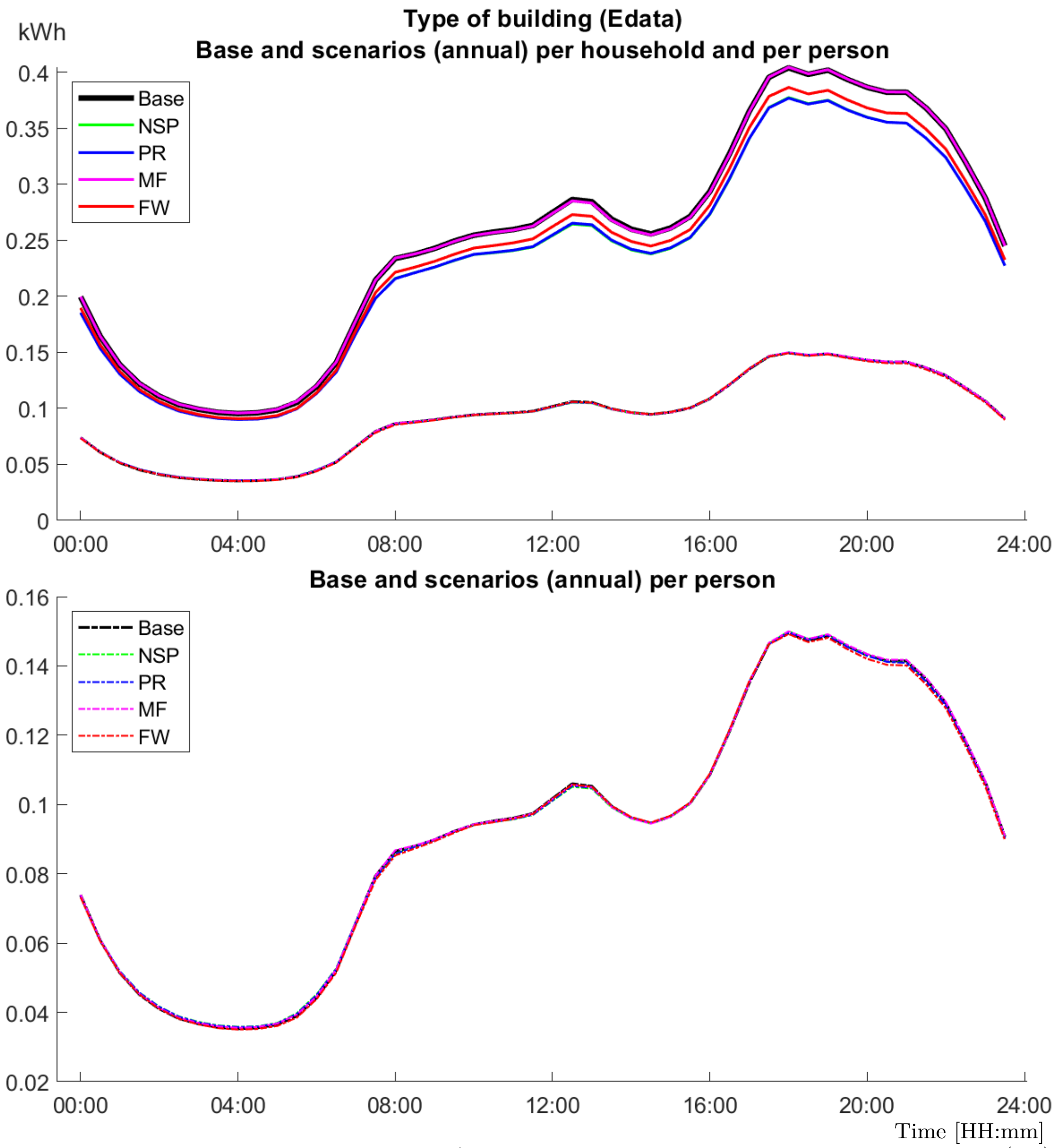


Figure 6.5.8.3: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Type of building'.

hold of flats is much lower than that of terraced and semi-detached houses, and that of detached houses higher for gas and much higher for electricity. Energy demand per person for detached houses is much higher than that of the other types of buildings, which are quite similar between them except for the electricity demand of flats, which is between that of detached houses and that of terraced and semi-detached houses. The line for flats is less smooth than the other lines, probably because the low presence of flats in the data (as explained in Section 6.2.1).

The projections per household for 'Type of building' show a decrease in energy demand for NSP and PR mainly due to their increased use of flats and decreased use of detached houses. This decrease is not large, however. FW shows a slight decrease in energy demand which is mostly attributed to the stark decrease in detached houses inhabited by the poor.

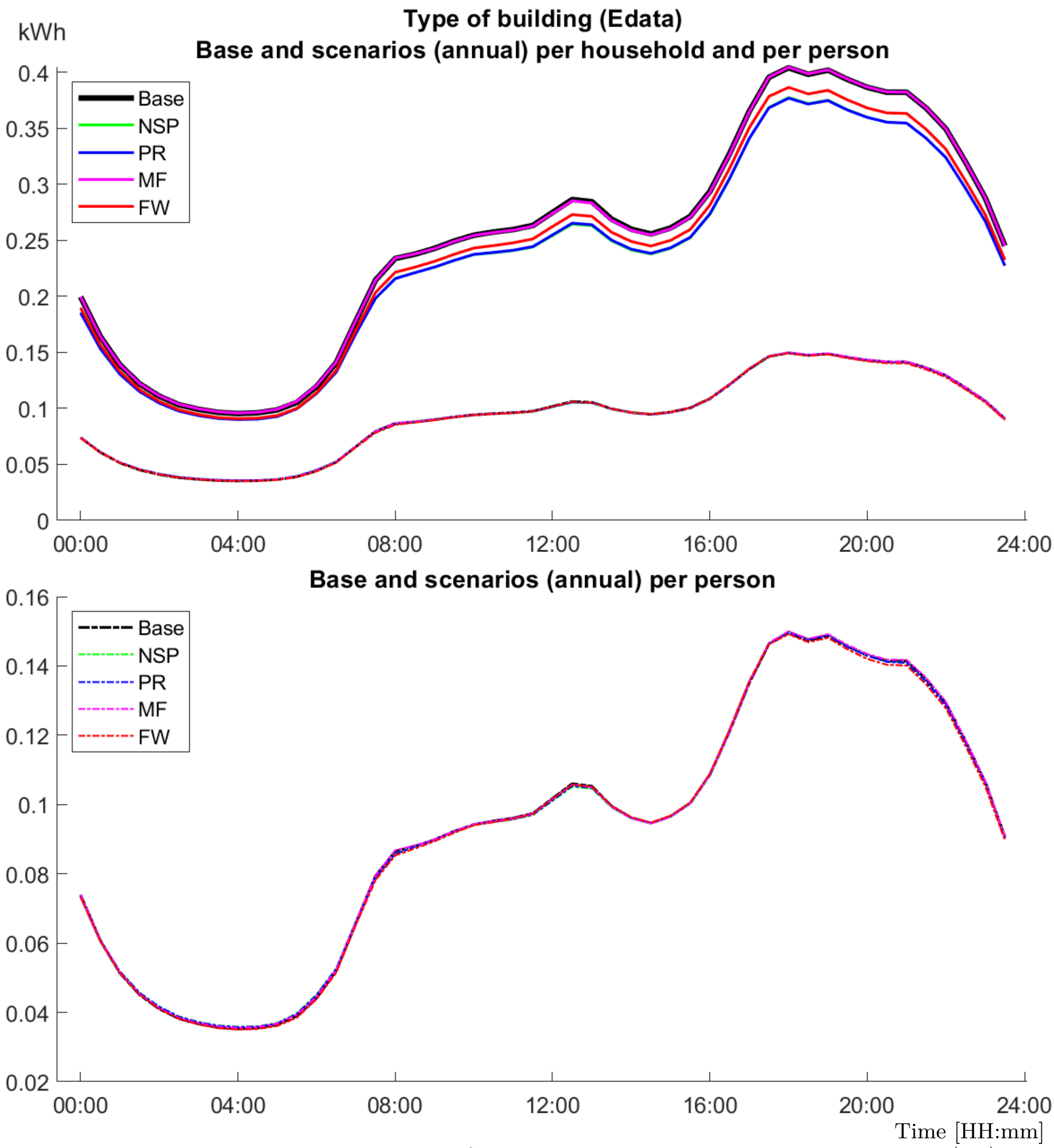


Figure 6.5.8.4: Base and projections of the annual gas demand per household (up) and per person (down) for 'Type of building'.

MF's projection is very similar to the base. It is also interesting to stress how similar the energy demands per person in the different scenarios and the base are.

6.5.9 Number of bedrooms

The relevant indicator from the extended DRC (Banchs-Piqué et al., 2020) is 'Average dwelling (usable) floor area', see its characteristics in Table 6.5.9.1. In the trial surveys there is a series of questions asking for the size of the dwelling but their answers are very unreliable. A large percentage of answers give strange results (either very large or very small dwellings) or have not answered these questions (Edata 58% and Gdata 51% did not answer). Therefore, the number of bedrooms (much easier to know by respondents) is

Table 6.5.8.3: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Type of building'.

Whole year											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4
AD	11.94	11.12	11.12	11.93	11.38	14.00	10.99	6.69	11.21	12.98	10.13
	4.42	4.42	4.42	4.43	4.40	4.32	4.41	4.41	4.27	4.53	4.27
WD	11.73	10.92	10.93	11.73	11.19	13.71	10.81	6.59	11.04	12.74	9.97
	4.34	4.34	4.34	4.35	4.32	4.23	4.34	4.34	4.21	4.44	4.20
WE	12.46	11.60	11.60	12.46	11.87	14.72	11.45	6.94	11.64	13.60	10.54
	4.61	4.61	4.61	4.62	4.59	4.54	4.59	4.58	4.44	4.74	4.44
kWh	Totals Gdata							Groups base Gdata			
AD	21.65	19.70	19.78	22.02	21.12	23.41	19.95	10.31	21.47	25.19	19.70
	7.55	7.50	7.52	7.58	7.63	7.40	7.61	7.22	7.31	8.29	7.40
WD	21.62	19.66	19.74	21.99	21.07	23.34	19.92	10.25	21.44	25.15	19.66
	7.54	7.49	7.50	7.56	7.61	7.37	7.60	7.17	7.30	8.27	7.38
WE	21.73	19.80	19.88	22.11	21.23	23.58	20.04	10.47	21.54	25.29	19.79
	7.58	7.54	7.55	7.61	7.66	7.45	7.64	7.33	7.34	8.32	7.43

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

used here as proxy. Other works using these data, such as (McLoughlin et al., 2012), also opted for using number of bedrooms as proxy for dwelling size.

Table 6.5.9.1: Characteristics of the indicator 'Average dwelling (usable) floor area' from the extended DRC (Banchs-Piqué et al., 2020).

Average dwelling (usable) floor area				
Measure *Base*	NSP	PR	MF	FW
	⇔	⇓	⇓	⇑ | ⇓
Average usable floor area in m^2 *95 m^2 (2013)*	Although people tend to live together in larger households than currently, the average dwelling's usable floor area decreases slightly. This is mainly due to the increased use of flats rather than houses and is exacerbated by the co-housing movement.	As the household size decreases and there is an increase in typically smaller dwellings (flats), the average dwelling floor area decreases notably.	The average dwelling floor area decreases. The main effect is, however, polarisation: with a strong increase in dwellings with smaller than 50 m^2 of internal floor space and an increase in those with larger than 110 m^2.	Rich: the average dwelling floor area for the rich is much larger than the current one (110 m^2 being close to their lower end). Poor: the average dwelling floor area for the poor is much smaller than the current one. Most of those with dwellings larger than 50 m^2 share them and many cannot even afford to live in formal developments.

The average dwelling area for dwellings with n number of bedrooms in UK can be found in the (Ministry of housing, communities and local government [MHCLG], 2018). However, this source adds together dwellings with 4 or more bedrooms. As the surveys ask up to 5 or more bedrooms and dwellings with 4 bedrooms constitute a large percentage of the dwellings in both trials (35% of Edata and 33% of Gdata), projections sort households with 4 bedrooms and with 5 or more bedrooms separately.

Table 6.5.9.2 shows the ratios of dwellings with n number of rooms for the data and their resulting average dwelling size. The average dwelling size of both data sets (115 m^2 and 111 m^2) are much larger than that of the base scenario (95 m^2). This may be because the dwellings with 4 and 5 or more rooms are grouped together in the (MHCLG, 2018). While the increase in square meters of adding one room from 1 to 3 bedrooms is of around 23 m^2 per room, this increase from 3 to 4+ rooms is of 61 m^2, much more than double.

Table 6.5.9.2: Number of households with n bedrooms for Edata and Gdata.

	Group ratio					Average	Average
Bedrooms	1	2	3	4	5+	number	size (m^2)
Edata	0.01	0.08	0.44	0.35	0.11	3.46	115
Erich	0.01	0.06	0.31	0.45	0.18		
Epoor	0.01	0.09	0.47	0.33	0.10		
Gdata	0.01	0.09	0.51	0.33	0.06	3.34	111
Grich	0.01	0.09	0.41	0.39	0.10		
Gpoor	0.01	0.08	0.55	0.31	0.05		
Average size (m^2)	44.3	65.6	89.6	150.3			

Last row shows the average size of dwellings with n rooms in UK from MHCLG (*Main report: figures and tables*, 2018). Last two columns show the average number of rooms and the average dwelling size in the samples.

Knowing the ratios of the groups in the samples, the ratios in the future scenarios can be derived by following the characteristics of the indicator and the process explained in the Box in Page 105. However, as the number of bedrooms must be used as proxy for dwelling size, some corrections have to be applied to account for the change in energy demand introduced by a change in the average size of households of n bedrooms. In NSP and PR, the dwellings tend to be smaller regardless of their number of rooms, therefore decreasing the energy demand (less need of heating, less space for appliances and more shared use). In MF there is no change in the size of households of n bedrooms and therefore the energy demand does not change. The poor in FW tend to divide rooms (or share them) (Banchs-Piqué et al., 2020), therefore the average size of the room, and so, their energy demand decreases; for the rich, the increase in size of their dwellings introduces an increase in energy demand. The ratios and corrections derived for the different groups in each scenario can be found in Table 6.5.9.3. The corrections are considered equal for both samples.

With these corrections and group ratios, the projections can be obtained using Expression 5.18. The resulting projections for the annual energy demand are shown in Figures

Table 6.5.9.3: Ratios and corrections derived for 'Number of bedrooms'.

	Edata				Gdata			
f_i	NSP	PR	MF	FWr|FWp	NSP	PR	MF	FWr|FWp
1	0.01	0.11	0.16	0.04|0.31	0.01	0.11	0.16	0.04|0.31
2	0.04	0.16	0.19	0.09|0.36	0.04	0.17	0.20	0.11|0.37
3	0.41	0.43	0.17	0.28|0.21	0.48	0.49	0.22	0.32|0.23
4	0.39	0.25	0.28	0.35|0.11	0.37	0.21	0.26	0.31|0.08
5+	0.15	0.05	0.20	0.24|0.01	0.10	0.02	0.16	0.22|0.01
k	0.95	0.95	1.00	1.30|0.80	0.95	0.95	1.00	1.30|0.80

6.5.9.3 (Edata) and 6.5.9.4 (Gdata), and can be compared with the energy demand of the different groups from Figures 6.5.9.1 and (Edata) and 6.5.9.2 (Gdata). Table 6.5.9.4 shows the resulting daily energy demand averages per household for the scenarios and the groups.

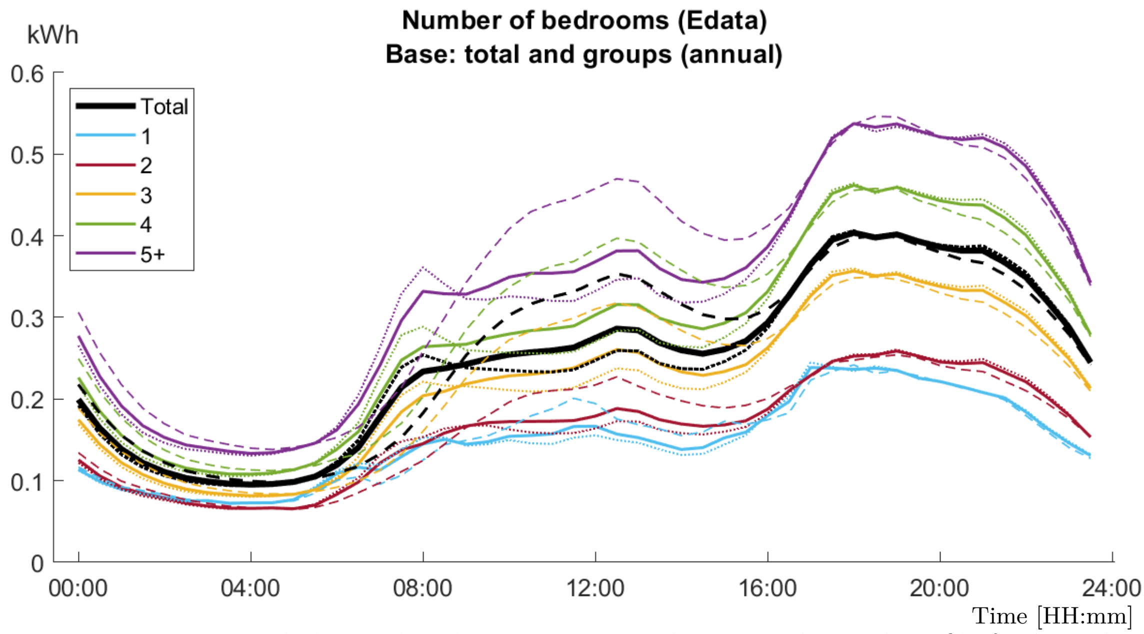


Figure 6.5.9.1: Base daily total and group average electricity demand profile for 'Number of bedrooms'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

For projections obtained using ratio-weighted sums, the behaviour of the base groups has to be analysed before analysing that of the projections.

In this case the expected behaviour is also seen, which is similar to that from 'Type of building': there is a clear distinction in the energy demand per household of the dwellings with different number of bedrooms with a gradient from less to more bedrooms, illustrated by almost parallel lines. The only exception is dwellings with 1 bedroom in Edata, their electricity demand is almost the same than that of 2 bedrooms dwellings. Another feature is that larger homes, especially those with 5+ bedrooms, show peakier profiles for gas; while their gas demand is higher during the day, this increase is even more marked in the morning and evening peaks. In terms of energy demand per person, it is almost constant for electricity with the clear outlier of 1 bedroom dwellings, for whom it is much larger

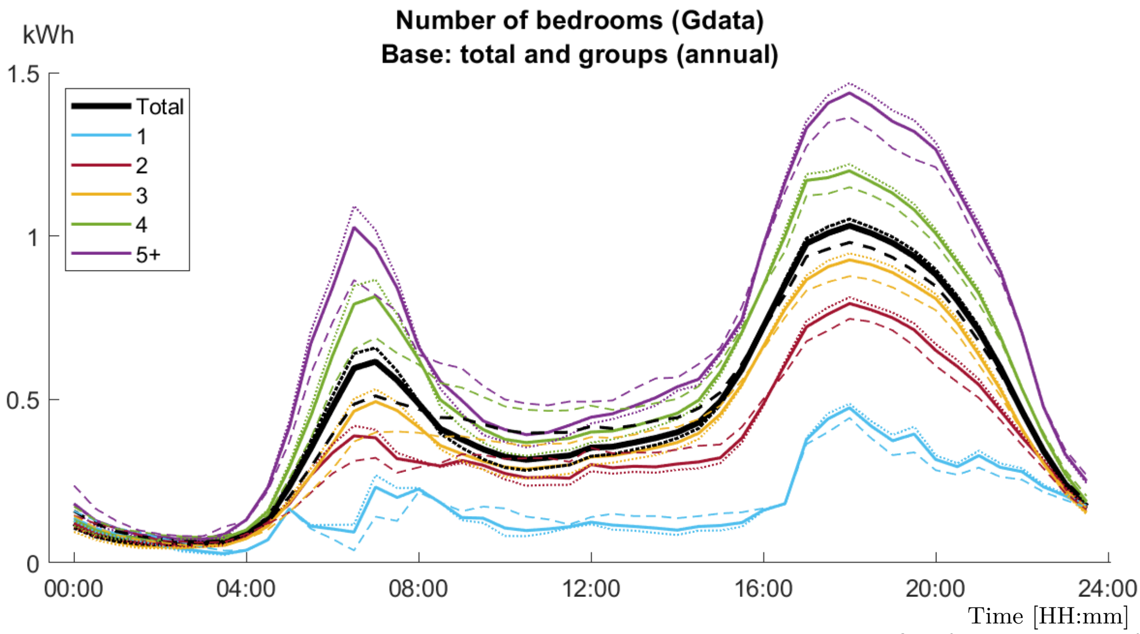


Figure 6.5.9.2: Base daily total and group average gas demand profile for 'Number of bedrooms'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

Table 6.5.9.4: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Number of bedrooms'.

Whole year												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	11.93	11.77	10.20	11.43	8.38	17.75	6.98	7.16	7.75	10.53	13.49	16.19
	4.42	4.20	4.27	4.59	4.05	5.68	3.80	6.33	4.44	4.36	4.37	4.63
WD	11.72	11.56	10.04	11.23	8.26	17.40	6.89	7.11	7.65	10.36	13.24	15.87
	4.34	4.13	4.20	4.52	3.99	5.57	3.75	6.29	4.38	4.29	4.29	4.54
WE	12.45	12.30	10.62	11.91	8.71	18.65	7.22	7.29	8.01	10.95	14.14	16.99
	4.61	4.39	4.44	4.79	4.20	5.97	3.93	6.44	4.59	4.53	4.58	4.86
kWh	Totals Gdata							Groups base Gdata				
AD	21.66	21.37	18.17	20.42	17.47	29.96	12.45	8.53	16.38	19.21	25.63	30.53
	7.55	7.18	7.21	7.82	7.41	9.57	6.48	7.96	8.92	7.03	8.03	7.61
WD	21.62	21.34	18.15	20.41	17.45	29.91	12.43	8.56	16.42	19.18	25.55	30.59
	7.54	7.17	7.20	7.82	7.40	9.55	6.48	7.99	8.94	7.02	8.01	7.62
WE	21.74	21.45	18.22	20.43	17.53	30.09	12.47	8.46	16.29	19.29	25.81	30.39
	7.58	7.20	7.23	7.82	7.43	9.61	6.50	7.89	8.87	7.06	8.09	7.57

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

(which fits with their demand per household). For gas, the variations are larger but with no clear trend, with 2 bedroom dwellings being the ones with largest demand per person and those with 3 bedrooms the ones with lowest demand per person. Here, again, the line for 1 bedroom dwellings is much rougher than the other ones, probably because the low presence of small dwellings in the data (as explained in Section 6.2.1). Another important feature is that 'Number of bedrooms' has the groups with highest and lowest gas demand

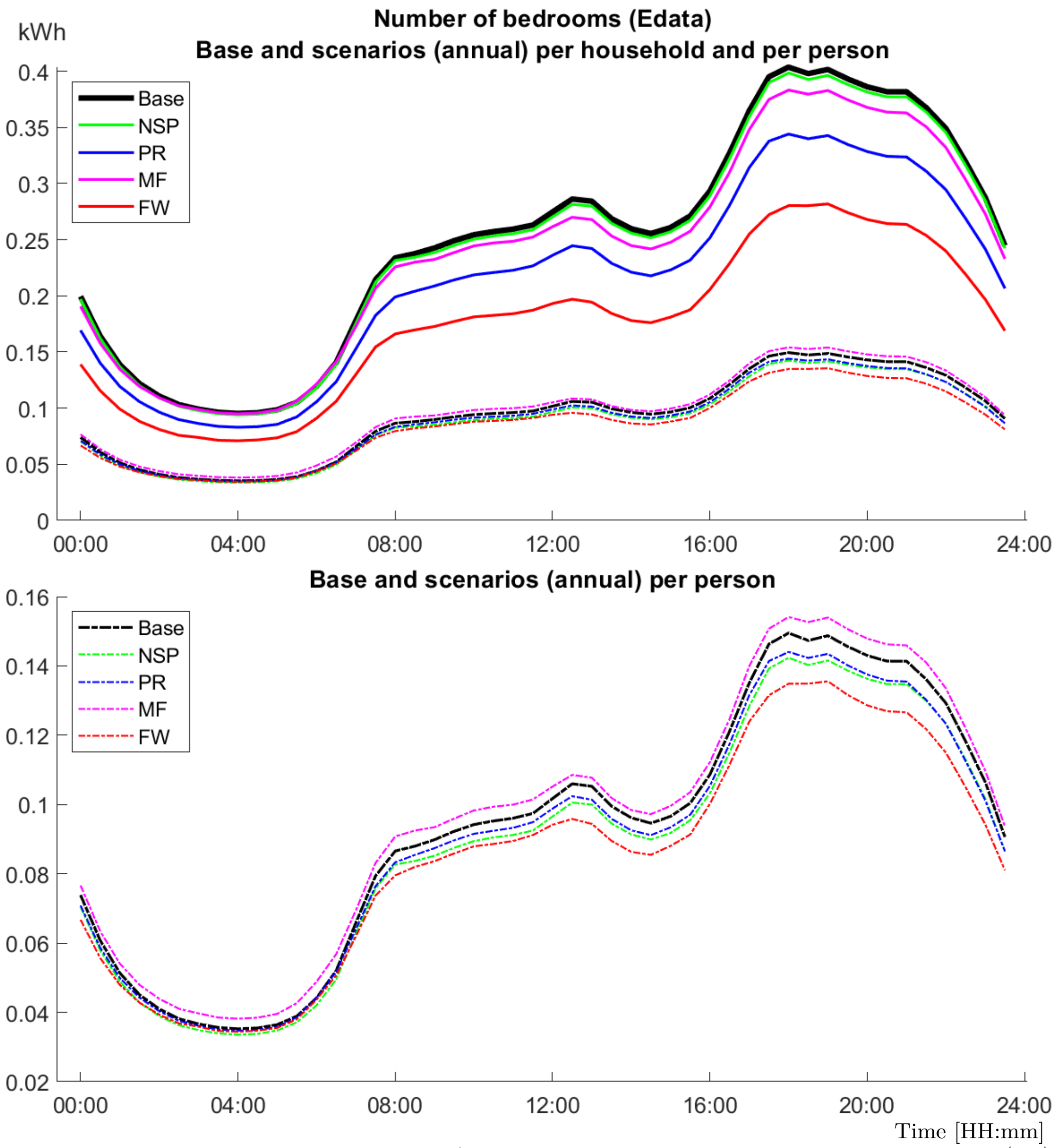


Figure 6.5.9.3: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Number of bedrooms'.

per household, groups with 5+ rooms and 1 room respectively. This behaviour seems normal because the main use of gas is for space heating, therefore it is normal that having more or less rooms to heat has an effect in its demand.

The projections per household for 'Number of bedrooms' show a decrease in energy demand for all scenarios. However, NSP's demand is almost equal to that of the base scenario and that of MF very similar too. PR shows a clear lowering in energy demand, which is very similar to that of FW for gas; for electricity, however, FW shows a much greater decrease of demand. The outlook is different for energy demand per person. Here, MF shows an increase for both, electricity and gas demands. The rest of the scenarios show a decrease in energy demand, although for all of them it stays very similar to that in the base scenario. The most relevant case is FW which, for electricity and part of the

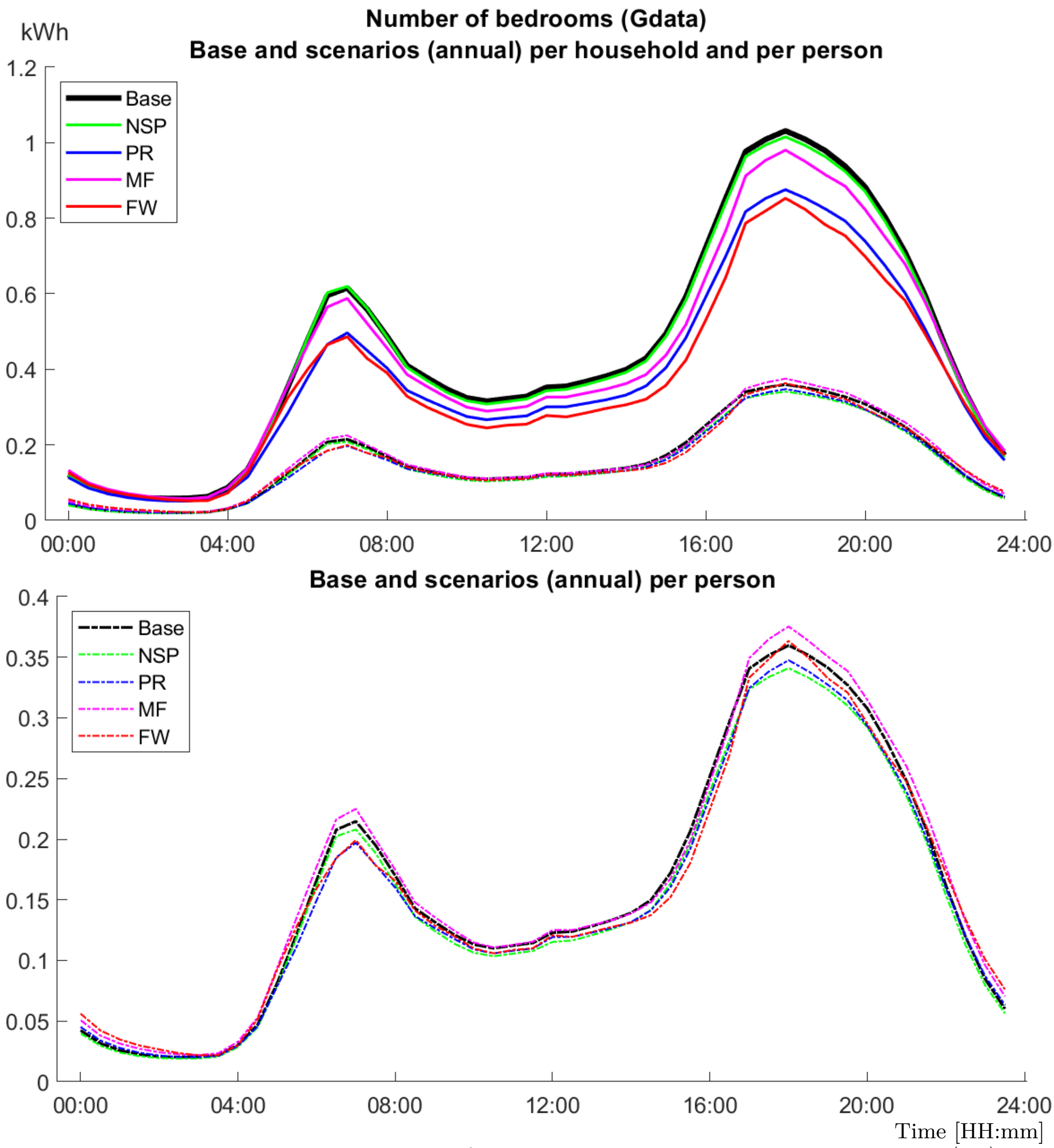


Figure 6.5.9.4: Base and projections of the annual gas demand per household (up) and per person (down) for 'Number of bedrooms'.

day for gas, is the scenario with lowest energy demand. However, in the evening peak, its gas demand is greater even than that of the base scenario.

6.5.10 Appliances ownership and use

The relevant indicator from the extended DRC (Banchs-Piqué et al., 2020) is 'Average number and frequency of use of electric appliances', see its characteristics in Table 6.5.10.1. Obviously, this variable applies only to Edata as appliances usually use electricity to run.

There are a number of questions related to this variable in the surveys of Edata. These questions first ask how many appliances the household owns and then there is a following

Table 6.5.10.1: Characteristics of the indicator 'Average number and frequency of use of electric appliances' from the extended DRC (Banchs-Piqué et al., 2020).

Average number and frequency of use of electric appliances				
Measure / *Base*	NSP	PR	MF	FW
	$\Downarrow$	$\Uparrow$	$\Uparrow$	$\Uparrow \mid \Downarrow$
N/A *Almost ubiquitous presence of washing machines, refrigeration and media appliances (2011)*	People tend to have and use appliances less than today.	Appliance use and ownership is similar to the current one, only slightly higher due to smaller households.	Dwellings have a larger number of appliances, and they are more intensively used than today.	Overall there are fewer appliances and these are less used because of the large weight of the poor population (35:65).

question asking for how often they are used. A punctuation system has been set in order to be able to define the groups. An explanation of the punctuation system can be found in Appendix C.2.2. The distribution of the points obtained per household is shown in Figure 6.5.10.1. Based on this distribution, the groupings are defined as: group 1 $(-\infty, 10]$, group 2 $(10, 20]$, group 3 $(20, 30]$, group 4 $(30, 40]$, group 5 $(40, \infty)$. The ratios of these groups in Edata are shown in Table 6.5.10.2.

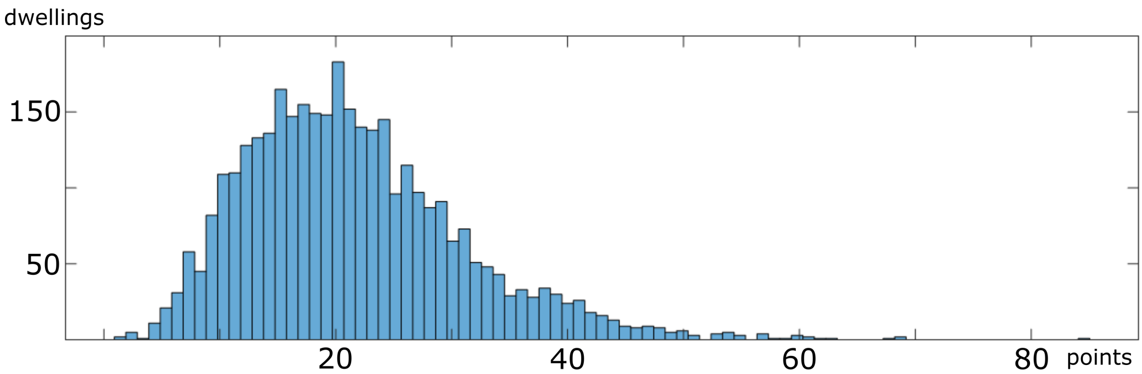


Figure 6.5.10.1: Distribution of points obtained per household for their use of appliances.

Table 6.5.10.2: Edata group ratios for 'Appliances ownership and use'.

	Group 1	Group 2	Group 3	Group 4	Group 5
Edata	0.11	0.42	0.32	0.11	0.04
Erich	0.05	0.34	0.36	0.17	0.08
Epoor	0.11	0.43	0.32	0.10	0.04

Based on the ratios of each group in Edata, the group ratios for the future scenarios are derived following the characteristics of the indicator and the process explained in the Box in Page 105. Table 6.5.10.3 presents them.

With these group ratios, the projections can be obtained using Expression 5.13. The resulting projections for the annual energy demand are shown in Figures 6.5.10.3, and can be compared with the energy demand of the different groups from Figure 6.5.10.2. Table

Table 6.5.10.3: Future scenarios ratios for 'Appliances ownership and use'.

	Edata			
	NSP	PR	MF	FWr|FWp
Group 1	0.51	0.09	0.04	0.01|0.91
Group 2	0.39	0.46	0.32	0.24|0.08
Group 3	0.09	0.34	0.41	0.43|0.01
Group 4	0.01	0.09	0.14	0.18|0.00
Group 5	0.00	0.02	0.09	0.13|0.00

6.5.10.4 shows the resulting daily energy demand averages per household and per person for the scenarios and the groups.

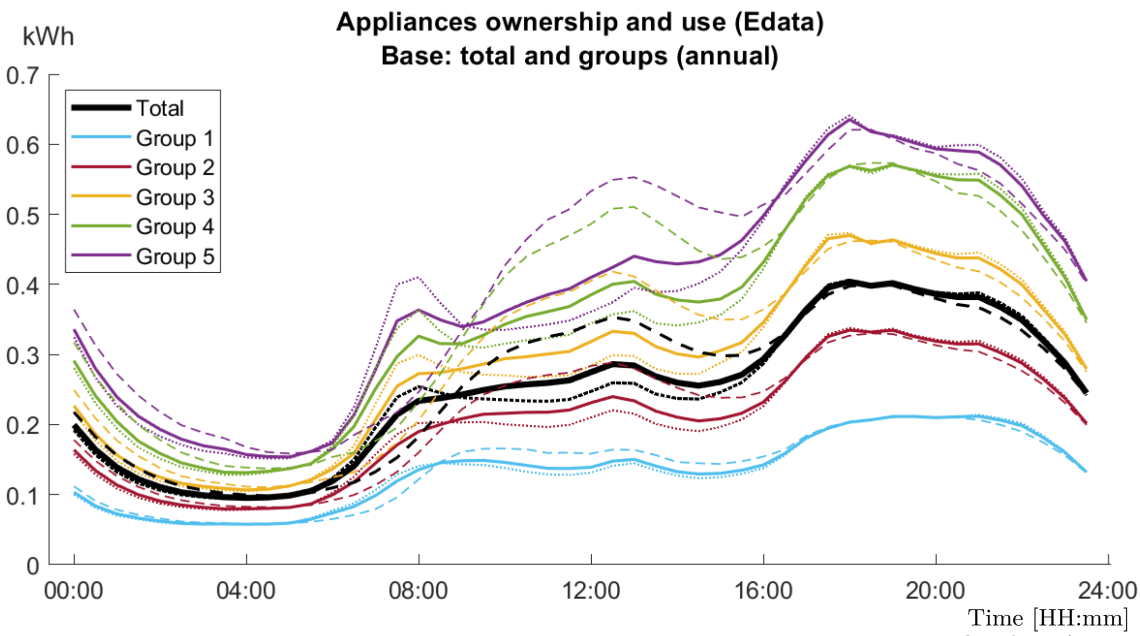


Figure 6.5.10.2: Base daily total and group average electricity demand profile for 'Appliances ownership and use'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

Table 6.5.10.4: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Appliances ownership and use'.

	Whole year											
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	11.94	8.54	11.69	13.11	7.78	14.83	6.73	6.45	9.84	13.78	16.90	18.74
	4.42	4.38	4.43	4.41	4.22	4.33	4.20	4.19	4.56	4.37	4.38	4.33
WD	11.73	8.40	11.48	12.88	7.68	14.54	6.66	6.37	9.67	13.53	16.58	18.44
	4.34	4.31	4.35	4.33	4.17	4.25	4.15	4.15	4.48	4.29	4.29	4.26
WE	12.46	8.86	12.20	13.69	8.05	15.58	6.92	6.63	10.28	14.40	17.69	19.49
	4.61	4.55	4.63	4.60	4.35	4.55	4.32	4.31	4.76	4.57	4.58	4.50

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

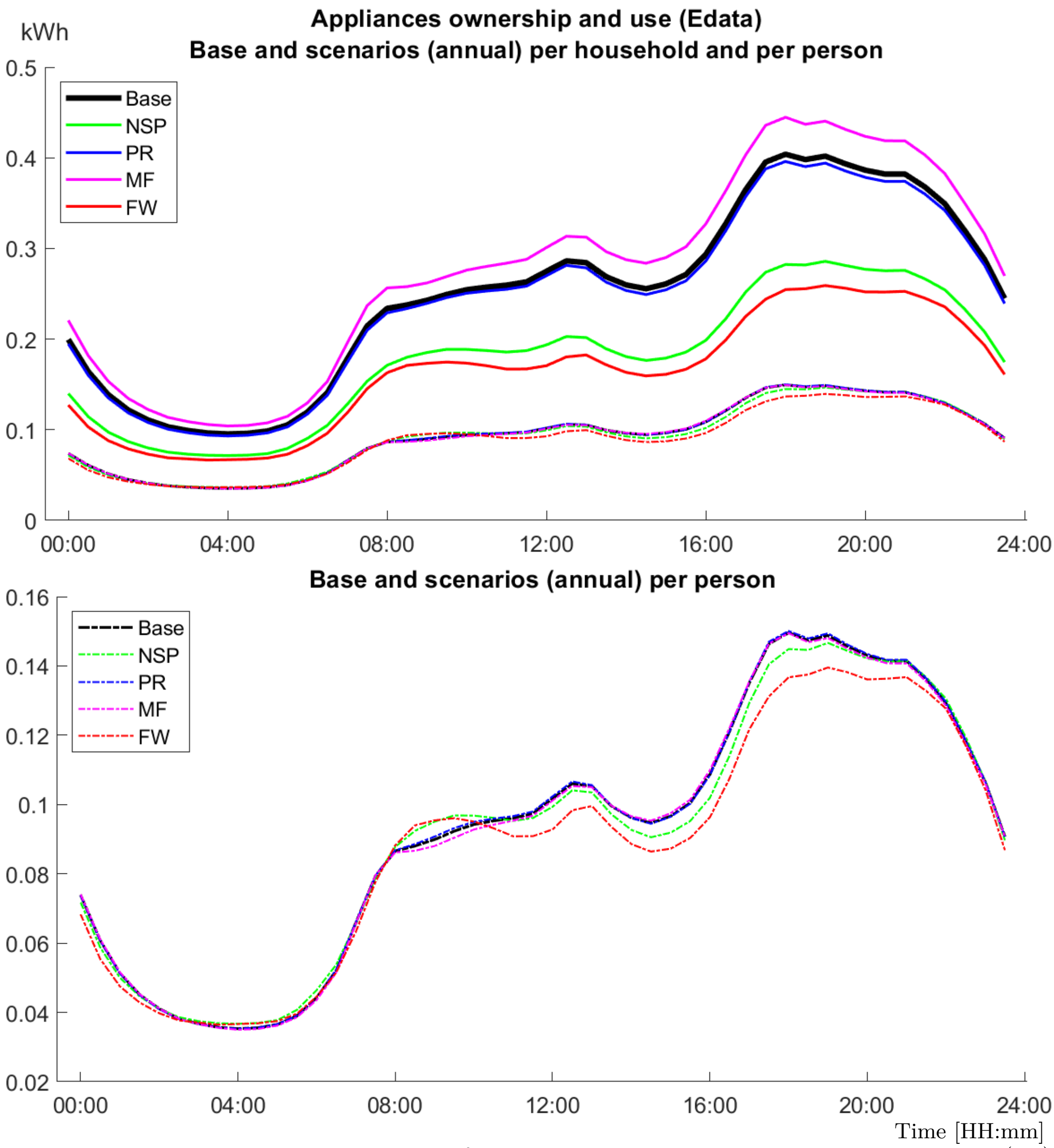


Figure 6.5.10.3: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Appliances ownership and use'.

For projections obtained using ratio-weighted sums, the behaviour of the base groups has to be analysed before analysing that of the projections.

Figure 6.5.10.2 and the 'Groups base' part of Table 6.5.10.4 show the importance of the ownership and use of electric appliances in the electricity demand of the households. The outline is similar to that of the previous two, with a clear distinction in the electricity demand per household of the different groups with a gradient from less to more appliance points, illustrated by almost parallel lines. The electricity demand per person is, however, much more stable, with group 1 having the lowest, group 2 the highest demands, and the rest being very similar. What this indicates is that group 1 contains a large percentage of households which cannot afford (or choose not to) own and use many appliances, while group 2 contains a large percentage of small households which make an intensive use of appliances due to not being able to share their usage. Another feature is that group 1 has the lowest and group 5 the highest average electricity demand per household of all the household groups sorted for any variable.

The projections for 'Appliances ownership and use' show a clear decrease in the electricity demand per household in the "extreme" scenarios, NSP and FW, while in the "business as usual" scenarios the electricity demand stays either very similar to the current, PR, or even higher, MF. The electricity demand per person follows similar trends but with much smaller differences between scenarios. A curious feature to note is that although in general the "extreme" scenarios demand less electricity, they show a higher morning peak than the other scenarios.

6.5.11 Energy poverty

The relevant indicator from the extended DRC (Banchs-Piqué et al., 2020) is 'Energy poverty', see its characteristics in Table 6.5.11.1. The definition of energy poverty in England according to (BEIS, 2013) is the following:

> "Fuel poverty in England is measured using the Low Income High Costs (LIHC) indicator. Under the LIHC indicator, a household is considered to be fuel poor if: they have required fuel costs that are above average (the national median level); [and] were they to spend that amount, they would be left with a residual income below the official poverty line."

Table 6.5.11.1: Characteristics of the indicator 'Energy poverty' from the extended DRC (Banchs-Piqué et al., 2020).

Energy poverty				
Measure *Base*	NSP	PR	MF	FW
	⇓	⇓	⇔	⇓ | ⇑
% of population in energy poverty *around 11% (2015)*	Better housing, the almost non-existence of poor people and the government's and society's engagement reduce energy poverty to almost zero.	The decrease in poor people, better housing and the engagement of governments contribute to a strong decrease in energy poverty.	Although inequality increases substantially, the high increase in gross domestic product is able to keep the level of energy poverty similar to the current one.	No energy poverty among the rich. Almost all among the poor are energy-poor.

In the surveys there are no questions which can inform about which households are energy poor following the definition above. However, they asked 1) if the house has not been kept adequately warm 1.1) because the occupants cannot afford to keep it as warm as they would like, or 1.2) because it is not well insulated, and 2) if they had to go without heating during the last 12 months through lack of money. Those households which answered any of these questions affirmatively are taken as energy poor. These are

344 households from the electricity trial (10%; and 8% from the rich and 10% of the poor), and 122 in the gas trial (9%; and 7% from the rich and 10% of the poor). It seems strange that a significant percentage of households of social classes A and B answered affirmatively to at least one of the questions. In addition, although as explained in Section 6.2.1 the energy poor are under-represented in the data samples, the percentage of energy poor in the samples is very similar to that of UK in 2015.

In any case, the group ratios in the future scenarios are derived following the characteristics of the indicator and the process explained in the Box in Page 105. These ratios are shown in Table 6.5.11.2.

Table 6.5.11.2: Future scenarios ratios for 'Energy poverty'.

	Edata				Gdata			
	NSP	PR	MF	FWr|FWp	NSP	PR	MF	FWr|FWp
Energy poor	0.00	0.01	0.10	0.00|1.00	0.00	0.01	0.09	0.00|1.00
No energy poor	1.00	0.99	0.90	1.00|0.00	1.00	0.99	0.91	1.00|0.00

With these group ratios, the projections can be obtained using Expression 5.13. The resulting projections for the annual energy demand are shown in Figures 6.5.11.3 (Edata) and 6.5.11.4 (Gdata), and can be compared with the energy demand of the different groups from Figures 6.5.11.1 and (Edata) and 6.5.11.2 (Gdata). Table 6.5.11.3 shows the resulting daily energy demand averages per household and per person for the scenarios and the groups.

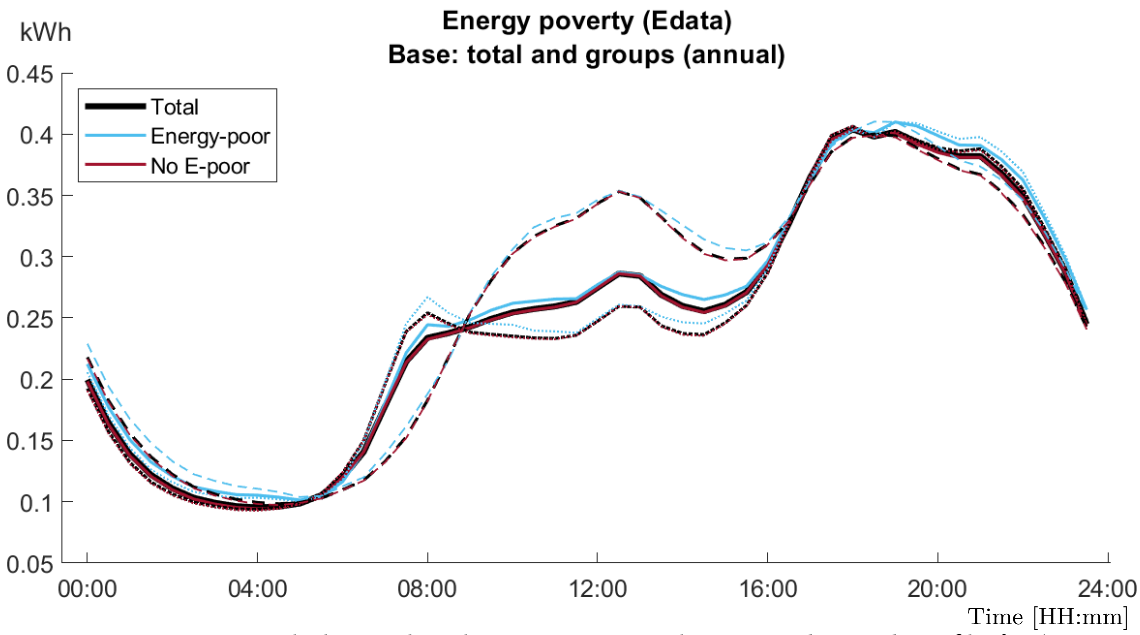


Figure 6.5.11.1: Base daily total and group average electricity demand profile for 'Energy poverty'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

For projections obtained using ratio-weighted sums, the behaviour of the base groups has to be analysed before analysing that of the projections. The difference between the groups is, in this case, very small. The energy poor group tend to use more electricity and

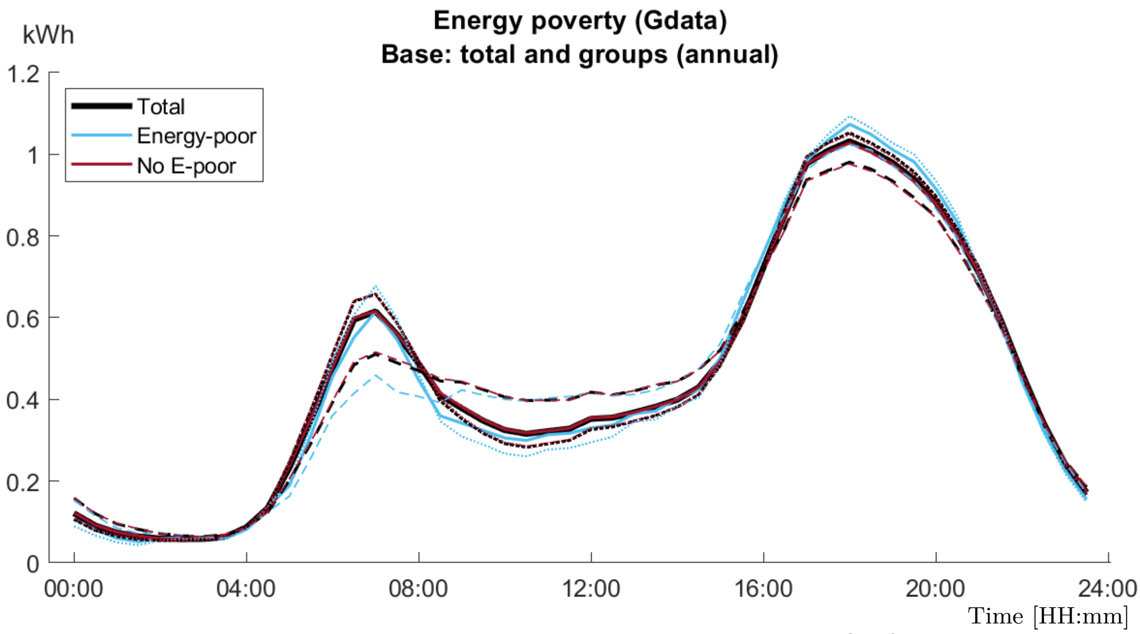


Figure 6.5.11.2: Base daily total and group average gas demand profile for 'Energy poverty'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

Table 6.5.11.3: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Energy poverty'.

Whole year									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
AD	11.94 4.42	11.90 4.40	11.90 4.40	11.94 4.42	12.34 4.61	13.80 4.32	12.12 4.65	12.26 4.58	11.90 4.40
WD	11.73 4.34	11.69 4.33	11.70 4.33	11.73 4.34	12.12 4.53	13.52 4.23	11.92 4.57	12.04 4.50	11.69 4.33
WE	12.46 4.61	12.42 4.60	12.43 4.60	12.46 4.61	12.88 4.81	14.51 4.54	12.64 4.85	12.80 4.78	12.42 4.60
kWh	Totals Gdata							Groups base	
AD	21.66 7.55	21.68 7.57	21.68 7.57	21.66 7.55	21.77 7.28	22.52 7.26	21.18 7.18	21.47 7.36	21.68 7.57
WD	21.63 7.54	21.65 7.56	21.65 7.56	21.63 7.54	21.71 7.26	22.45 7.23	21.13 7.16	21.42 7.34	21.65 7.56
WE	21.74 7.58	21.75 7.60	21.75 7.60	21.74 7.58	21.91 7.32	22.70 7.31	21.31 7.23	21.61 7.40	21.75 7.60

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

less gas, although their night peak is higher. It is probable that these small differences are due to bad groupings: the ratio of energy poor in the samples is very similar to that reported for UK in 2015 while, as seen in Section 6.2.1, energy poor households are under-represented in the samples. Bad groupings would also explain the large amount of energy poor within social classes A and B in the samples.

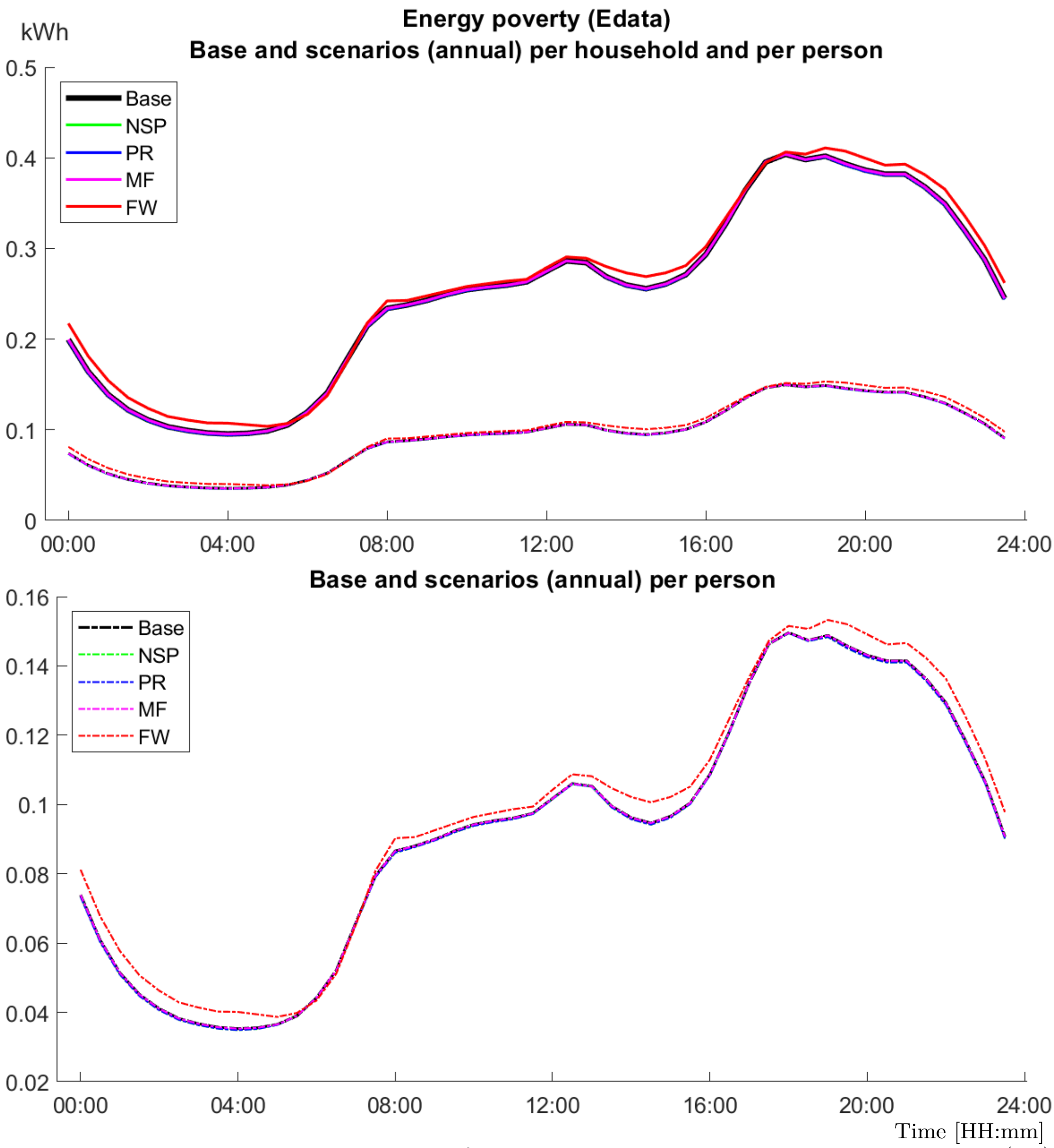


Figure 6.5.11.3: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Energy poverty'.

Due to the small differences between groups, the projections per household for 'Energy poor' do not show large differences. Only FW shows a slight increase in energy demand per household and a slight decrease per person. The other scenarios follow almost exactly the data samples.

6.5.12 Household size

The relevant indicator from DRC (Lombardi et al., 2012) is 'Average household size', see its characteristics in Table 6.5.12.1.

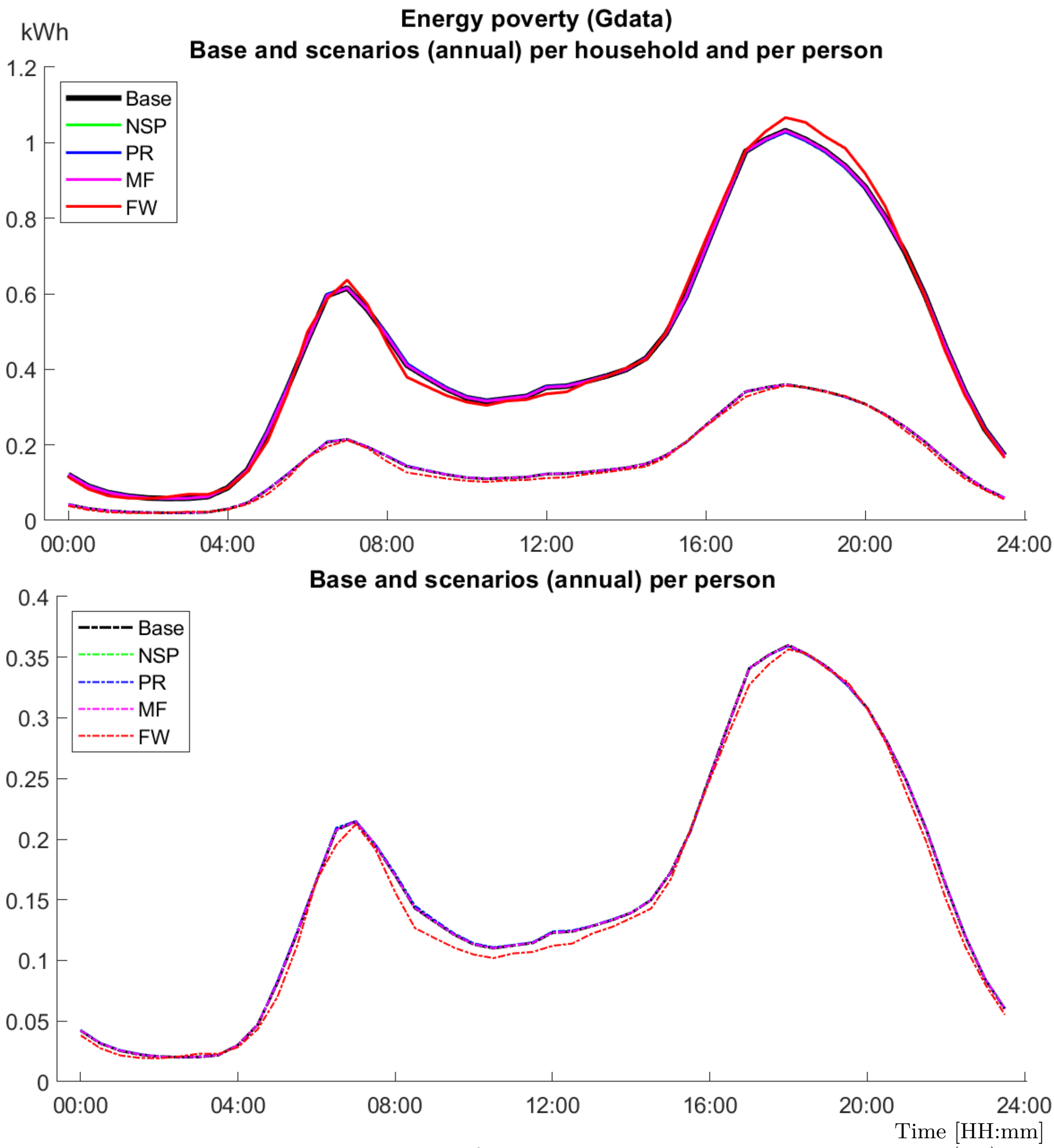


Figure 6.5.11.4: Base and projections of the annual gas demand per household (up) and per person (down) for 'Energy poverty'.

The size of each household from the data samples can be obtained combining two questions from the surveys, they ask for the number of occupants over and under 15 years old. When they are combined, the ratios of each group can easily be obtained. They are shown, together with the average household size in each sample, in Table 6.5.12.2. Following the characteristics of the indicator and the ratios in the base scenario, the ratios in the future scenarios can be derived following the process explained in the Box in Page 105. They are shown in Table 6.5.12.3.

With these group ratios, the projections can be obtained using Expression 5.13. The resulting projections for the annual energy demand are shown in Figures 6.5.12.3 (Edata) and 6.5.12.4 (Gdata), and can be compared with the energy demand of the different groups

Table 6.5.12.1: Characteristics of the indicator 'Average household size' from DRC (Lombardi et al., 2012).

Average household size				
Measure *Base*	NSP	PR	MF	FW
	⇑	⇔	⇓	⇓ | ⇑
People/ household *2.4*	Although population is ageing, strong social and environmental drivers mean co-housing and living with extended family or in multiple family units is commonplace.	Trend towards smaller household sizes continues (exacerbated by ageing population). Core values of individualism mean people do not want to share accommodation.	Trend towards smaller household sizes continues (exacerbated by ageing population). Core values of individualism mean people do not want to share accommodation.	Average household size may increase for the poor out of necessity, and decrease for the rich out of choice.

Table 6.5.12.2: Base ratios for the 'Household size'.

Group ratios for 'Household size'							
Number of occupants	1	2	3	4	5	6+	Average
Edata	0.21	0.33	0.17	0.17	0.08	0.04	2.7
Erich	0.11	0.28	0.18	0.24	0.13	0.07	
Epoor	0.23	0.34	0.17	0.15	0.08	0.04	
Gdata	0.16	0.31	0.20	0.21	0.09	0.04	2.9
Grich	0.13	0.27	0.20	0.24	0.11	0.05	
Gpoor	0.18	0.32	0.19	0.19	0.08	0.04	

Table 6.5.12.3: Future scenarios ratios for 'Household size'.

Number of	Edata				Gdata			
occupants	NSP	PR	MF	FWr|FWp	NSP	PR	MF	FWr|FWp
1	0.13	0.23	0.26	0.18|0.07	0.09	0.17	0.20	0.19|0.06
2	0.24	0.34	0.36	0.33|0.17	0.22	0.32	0.34	0.31|0.17
3	0.22	0.17	0.18	0.20|0.23	0.23	0.20	0.21	0.22|0.24
4	0.20	0.15	0.15	0.21|0.22	0.24	0.19	0.19	0.21|0.23
5	0.13	0.08	0.04	0.06|0.18	0.14	0.09	0.05	0.06|0.18
6+	0.08	0.03	0.01	0.02|0.13	0.08	0.03	0.01	0.01|0.12
Household size	3.2	2.6	2.4	2.5|3.7	3.4	2.8	2.6	2.7|3.7

from Figures 6.5.12.1 and (Edata) and 6.5.12.2 (Gdata). Table 6.5.12.4 shows the resulting daily energy demand averages per household for the scenarios and the groups.

For projections obtained using ratio-weighted sums, the behaviour of the base groups has to be analysed before analysing that of the projections.

In this case one can see that the household size is directly linked to the energy demand per household. For the electricity demand it is very clear, each group forming almost parallel lines with clear separation between them. For gas, the differences are much less constant, leading to a more complex pattern, but the progression is clear as well. In terms

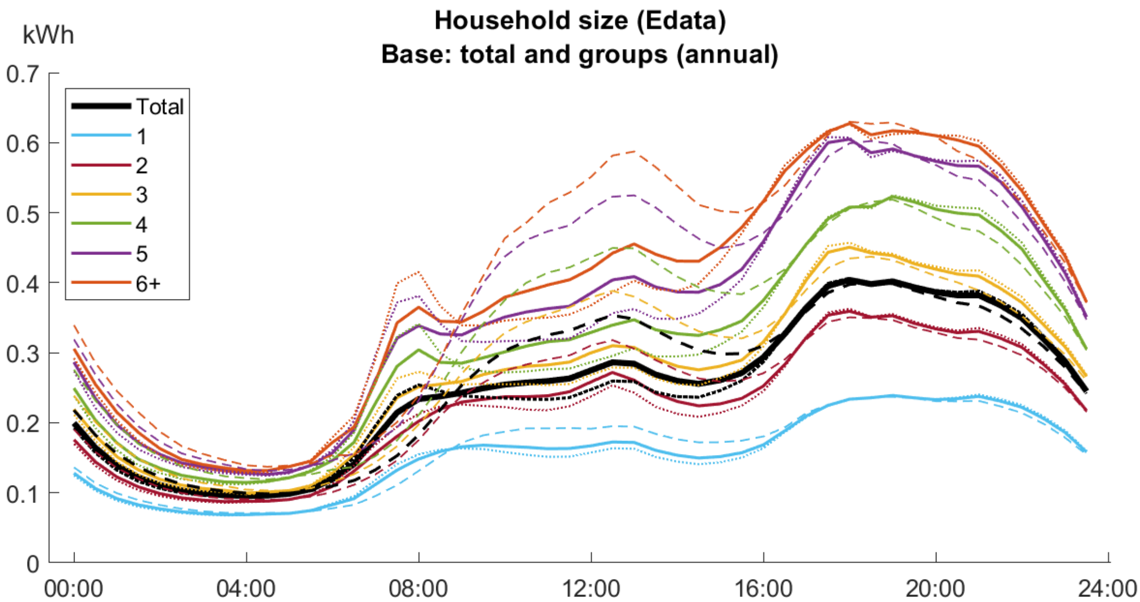


Figure 6.5.12.1: Base daily total and group average electricity demand profile for 'Household size'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

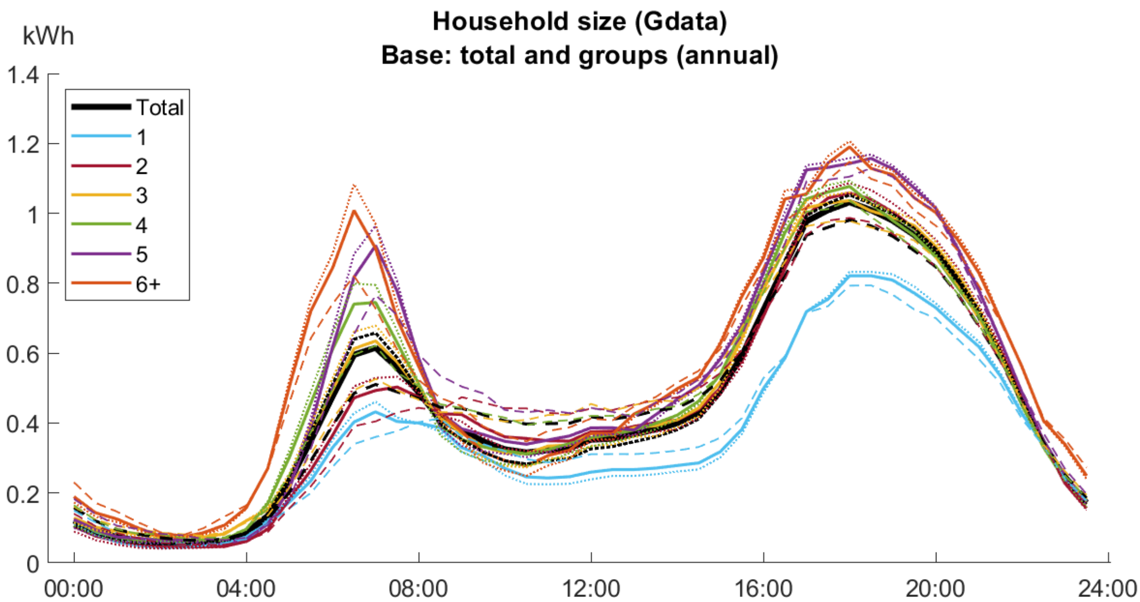


Figure 6.5.12.2: Base daily total and group average gas demand profile for 'Household size'. Solid lines correspond to AD, dotted lines to WD, and dashed lines to WE.

of energy demand per person, the trend is reversed (the larger the household, the less energy demand per person) but as clear as in energy demand per household. In fact, in terms of energy demand per person, household size is the variable which (inversely) correlates the most with it, having both the lowest electricity and gas demands per person (in 5+ member households) and both the highest electricity and gas demands per person (in 1 member households).

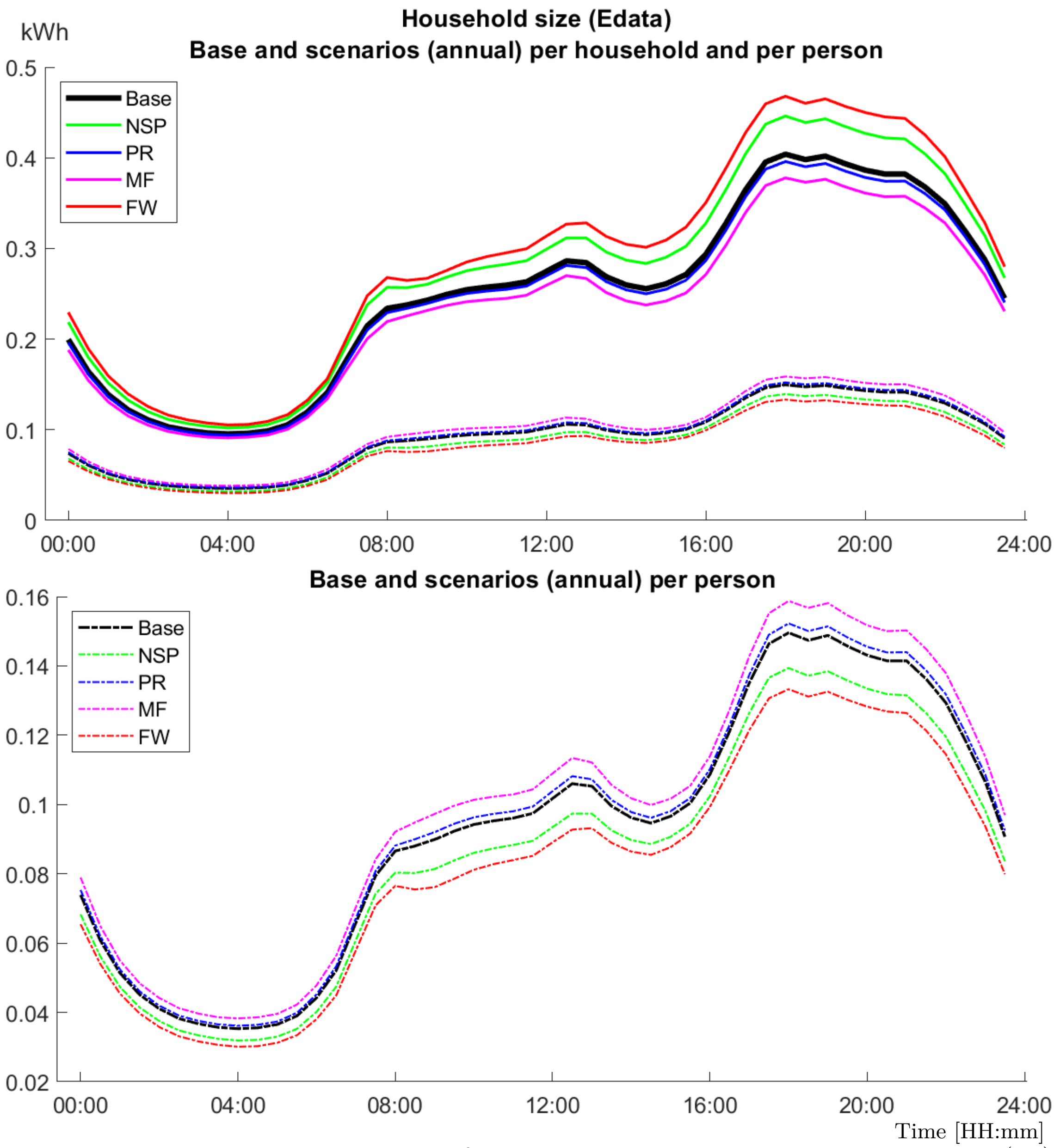


Figure 6.5.12.3: Base and projections of the annual electricity demand per household (up) and per person (down) for 'Household size'.

The projections for 'Household size' show expected profiles. In the scenarios where the household size increases, FW and NSP, the energy demand per household increases (especially electricity) and the energy demand per person decreases. PR follows with almost the same energy demand patterns as the base scenario, only slightly lower per household and higher per person, and MF is similar to PR but with more difference with the base scenario.

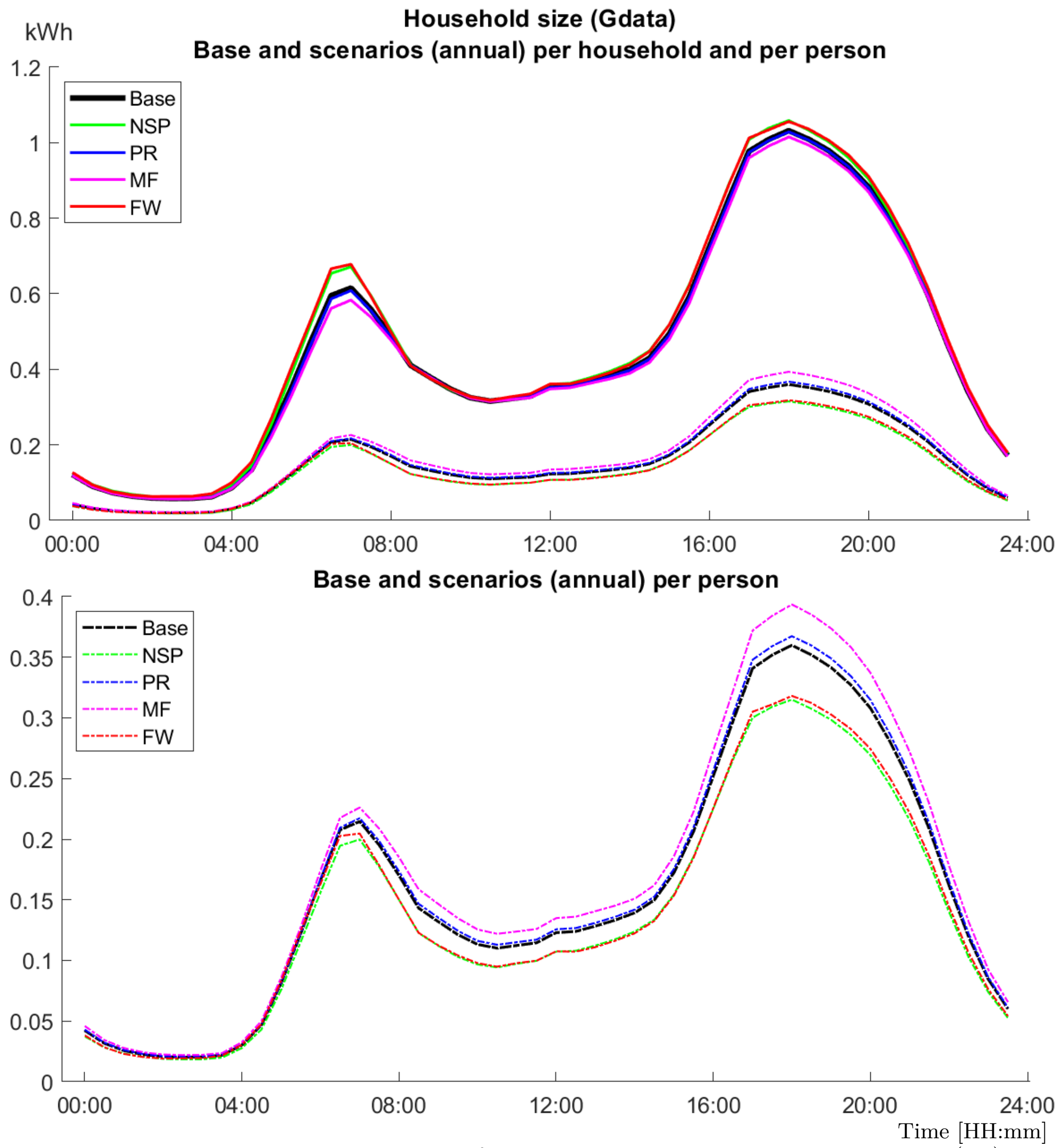


Figure 6.5.12.4: Base and projections of the annual gas demand per household (up) and per person (down) for 'Household size'.

6.6 Summary, discussion and conclusions

The aim of this chapter was to use the tool developed in Chapter 5 to project household energy demand data into the scenarios from DRC, which were supplemented with details related to households and their use of energy in Chapter 4. The projections were obtained for a comprehensive set of variables determining household energy demand. To do that, data from the CER smart metering trials were used (CER, 2012a, 2012b). These data provide not only the power demanded by each household in half an hour periods, but also metadata about the households needed to obtain the projections. Although the metadata is very comprehensive, it was impossible to obtain projections for two impor-

Table 6.5.12.4: Base, projections and group's annual daily average electricity (Edata) and gas (Gdata) demands for the variable 'Household size'.

Whole year													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5	G6
AD	11.94	13.09	11.71	11.21	13.73	12.56	13.91	7.42	10.64	12.94	14.95	17.33	18.54
	4.42	4.09	4.50	4.71	3.91	4.65	3.80	7.42	5.32	4.31	3.74	3.47	3.09
WD	11.73	12.85	11.51	11.02	13.48	12.31	13.65	7.32	10.47	12.73	14.64	16.98	18.17
	4.34	4.02	4.43	4.63	3.84	4.56	3.73	7.32	5.23	4.24	3.66	3.40	3.03
WE	12.46	13.68	12.22	11.69	14.36	13.19	14.54	7.68	11.08	13.46	15.73	18.20	19.46
	4.61	4.28	4.70	4.91	4.09	4.88	3.97	7.68	5.54	4.49	3.93	3.64	3.24
kWh	Totals Gdata							Groups base Gdata					
AD	21.66	22.44	21.56	21.21	22.57	21.77	22.56	16.97	21.41	22.36	22.85	24.64	26.52
	7.55	6.68	7.70	8.22	6.78	8.15	6.17	16.97	10.71	7.45	5.71	4.93	4.42
WD	21.63	22.41	21.53	21.17	22.52	21.67	22.54	16.90	21.40	22.29	22.85	24.55	26.66
	7.54	6.67	7.69	8.21	6.77	8.12	6.16	16.90	10.70	7.43	5.71	4.91	4.44
WE	21.74	22.50	21.65	21.30	22.68	22.01	22.63	17.17	21.45	22.51	22.86	24.88	26.17
	7.58	6.70	7.73	8.26	6.82	8.24	6.18	17.17	10.72	7.50	5.72	4.98	4.36

First row of each type of day shows energy demand per household and second row of type of day shows energy demand per person.

tant variables determining the energy demand of households, 'Time spent at home' and 'Microgeneration'.

Before proceeding to develop the factors needed to obtain the projections for each variable, and to actually obtain these projections, the details of the projections needed to be defined (periods, averages, etc.). This was done in the first section of this chapter. In the next section, the data and the trials were they were obtained were analysed and compared with UK values, what showed that the data are not representative for the UK. And before showing the development and the projections of the variables, a short explanation of the code written to manage the data was given, followed by a brief analysis of the behaviour of the energy demand in the samples.

The process of grouping sub-samples of data based on their distinct "values" with respect to a variable and analyse the behaviour of the groups, and repeating that analysis for different variables has proven to provide good insights about the characteristics of the data. For example, this process has shown which of the researched variables influence most the demand for electricity and gas. It also hinted that either some groupings could be better defined or the information of the metadata be more accurate, as the difference in energy demand between the groups of certain variables was found to be smaller than expected. This could be further researched by performing the same analysis to other data samples and comparing their outcomes.

From these analyses, it was found that the variable with more influence in the electricity demand per household in Edata is 'Appliances ownership and use'. This variable has the groups with highest and lowest electricity demand per household (group with the most and the least appliance use points respectively). However, it is interesting to note that the variable with the highest and lowest electricity demands per person was 'Household size' (households with one and with five or more members respectively). This fits with the fact that the more appliances a household has and use, the more electricity it demands, regardless of its size. However, depending on the size of the household there is more or less shared usage of appliances: in one-member households there cannot be any shared use of appliances which, therefore, makes their electricity demand per person higher, while in large households the opportunity to share appliances usage is huge, making their average electricity demand per person smaller. Note that the group with highest electricity demand per person (7.42 kWh) demands only 15% more electricity than the group with lowest electricity demand per household (6.45 kWh). This is probably because the main part of these groups overlap, being one-member households who cannot share the use of appliances with anyone.

In terms of gas demand, the variable with the groups with highest and lowest gas demands per household is 'Number of bedrooms' (5+ bedrooms and 1 bedrooms respectively). And the variable with the groups which show the most and the least gas demand per person is again 'Household size'. This also fits with what was expected because gas is mainly used for space heating. Therefore, the more rooms there are to heat, the more gas is demanded, quite but not totally regardless the household size. And the reverse is also true, almost regardless the number of occupants, a larger dwelling needs more gas to be heated. Therefore, the more occupants it has, the more this gas demand is shared between them.

It is important to note that some of the groups are created with a degree of subjectivity because their values are not discrete; for example those for 'Appliances ownership and use' or 'Percentage of children at home'. And also that, although the "values" of some groups are discrete, their realities may be less so; for example in 'Household size', where a couple with or without a baby would fall in two different groups although their gas demand may not change due to that baby. In spite of this, these kind of analyses provide useful information.

Focussing on the projections, what is more salient is that the projections based on (or containing) corrections are mostly the ones showing larger differences with the base. However, when the groups defined for a variable express large differences in their energy demands, their projections can also show large differences (*e.g.* 'Appliances ownership and use').

It is also clear that the analysis of the projections for each variable can give important insights into the effects of possible evolutions of these variables in the future. However, this analysis cannot only be superficial, as it could lead to erroneous conclusions. It is possible that a particular variable is linked, in the given data or in general, to other underlying variables. In the present case the underlying variable is often 'Household size'. Then, although the energy demand per household in a particular scenario shifts in one direction, its energy demand per person may shift in the opposite direction. Therefore, it is important to not only obtain projections for the household energy demand, but also for the energy demand per person. In a general case, one would need to study what underlying variables may be important and establish some kind of control for their effect. For this reason, also the energy demand per person has been projected here.

In the analysis of the projections obtained, it has been clear that projections consisting only of corrections do not present any surprising results; they show the same profile as the base shifted upwards or downwards with the derived factor. The behaviours of the projections with groups are more interesting and intricate. In some cases, especially when a given scenario is greatly shaped by a group with some particular behaviour, this behaviour may be very marked in the scenario (*e.g.* the morning peak in gas demand of FW in the projection for 'Percentage of children at home'). In general, however, the differences between scenarios are not very large when only ratio-weighted sums are used to obtain them. This has two causes, 1) the difference in the energy demand between groups is usually not large, and 2) even when it is large, the differences in the group ratios between scenarios are not usually dramatic. Therefore, only in few occasions the resulting projections are markedly different.

An important point is that some projections for FW are very likely to present an energy demand much higher than they would if the data contained information about the energy demanded in informal settlements. However, as explained in Section 6.2.1, for planning purposes it is better to err on the side of too much rather than too little.

The differences between scenarios are usually larger for electricity demand than for gas demand. This may be because electricity is mainly used to power appliances while gas for heating the dwelling, plus the lack of projections for some variables with significant effect on gas demand. Heating, *i.e.* the use of gas, is mostly non-avoidable; a base load is needed by all households to keep their dwellings habitable. On the other hand, the use of appliances, *i.e.* electricity, can be more discretionary. In addition, some of the variables which influence gas demand the most are difficult to define and measure. For example, some households may keep their dwellings warmer than others, but such a variable would be difficult to define (different rooms may be kept at different temperatures, these temperatures may differ depending on who occupies the room and the outside temperature, etc.) and to measure (a survey would probably not give reliable information and thermostat data may be difficult to obtain).

As the definition of the variables is constrained by the metadata available, the information that some of the variables convey is different than intended; sometimes giving less information, sometimes shifting the information they give. The variable 'Percentage of children in the household', for example, is the closest variable to convey the age distribution from the household members that could be defined. However, this definition only informs about the relation between occupants younger than 15 years old and the rest of occupants. As a side note, this definition has a different correlation to 'Household size' than age distribution would, which has an impact in Chapter 7. Another example is 'Number of bedrooms', which is a proxy for the usable floor area of the dwelling. This variable conveys significantly less information than the proxied variable, as its information is much coarser.

Clearly, the groups and variables chosen to obtain projections did not manage to completely untangle the variables. 'Household size' certainly affects many other variables. Other variables probably also have underlying connections. It is impossible, however, to obtain a set of independent variables which determine all the factors involved in the energy demand of households without leaving any gap. Here, an attempt to cater for all these determinants with the minimum amount of dependency between variables has been made. However, the projections obtained for particular variables have different degrees of dependency to other variables. One option is to take these dependencies into account when aggregating projections. Still, this comes with a degree of subjectivity, since giving an exact value to these dependencies is a very challenging task. Two examples of aggregates with different weights for the projections of different variables are presented in the next chapter. Their aim is not to produce a final "result" for the energy demanded in each scenario, but to discuss the effect of the weights and the information that can be obtained from these aggregates. In addition, these aggregates demonstrate that with the tool developed in Chapter 5, one can study an approximation to the general behaviour of the energy demand in a scenario in addition to studying the effect that a particular variable has in the energy demand of that scenario. Then, comparing these general behaviours in each scenario to the original data, the evolution of the energy demands in each scenario can be obtained.

Chapter 7

Aggregates of projections

The future's not what it used to be.

— Mickey Newbury

In this chapter the projections obtained above are aggregated by two distinct methods. This allows an analysis of the projections' robustness. Before that, the methods chosen to aggregate projections are briefly discussed, the aggregates obtained, and the evolutions of the energy demands in each scenario presented. Finally, it analyses and compares the aggregates, and presents a discussion, examples of the usefulness of the aggregates to improve planning, a comparison with the indicator 'Domestic energy demand' from DRC, and a summary.

7.1 Introduction to aggregates

In the previous chapter, the tool developed in Chapter 5 has been used to obtain projections of Edata and Gdata into the future scenarios from DRC for a comprehensive set of variables defining the energy demand of households. Each projection simulates the effects on the data samples of a particular variable changing its behaviour to follow the characteristics of the future scenarios. For a given scenario, therefore, each projection conveys the implications of varying a single variable. In order to get a more general picture of the future scenario, these projections can be aggregated to form a single aggregate. Although developing a "correct" method to aggregate projections is out of the scope of this thesis, it is interesting to briefly explore what such aggregates can tell us about the household energy demand in the future scenarios[1].

[1]Note that the very aggregation method chosen introduces subjectivity in the analysis of the aggregates produced (Nardo et al., 2005; Rowley et al., 2012).

Aggregates can be obtained, for example, by means of a weighted sum of the different projections. The simplest form of weighted sum is the average, *i.e.* avoid giving explicit weights to the projections (or, more precisely, giving each projection the same weight). The decision of not giving any explicit weight to the projections may easily be invisible for the reader if it is not acknowledged, as there is no need to explicitly reason or derive anything. Indeed, one of the advantages of explicitly weighting the projections is that the weights make obvious and transparent the underlying construction of the aggregate. In the end, weights, either explicit or implicit, are essentially value judgements which affect the end result. Therefore, it is important to explicitly and transparently state them and, if they are implicit, make an extra effort to clarify that equal weights have been used (Nardo et al., 2005; Rowley et al., 2012).

In the next section, two aggregates of the projections for each scenario are obtained for electricity and for gas. One aggregate is a simple average of the projections, *i.e.* a weighted sum where all the weights are equal. The other one is a weighted sum, with the weights attempting to account for the dependencies and relative importance of each variable in each scenario. In further sections, the differences between these aggregates are analysed and discussed.

As seen in the previous chapter, the behaviour of the energy demand projected into the different scenarios varies depending on whether it is a per household or per person projection. This is because the household size dynamics of the different groups are not homogeneous. This not only leads to differences in the average household size of the different groups, but also in the average household size of the projections obtained with ratio-weighted sums in different scenarios. The resulting average household size for the scenario aggregate may have, then, nothing to do with that conveyed by its characteristics. This does not mean that the aggregate is "wrong". The agents of the projections are households, therefore the projections per person are only an accessory to aid in their analysis. A clear example of this is the projection for 'Appliances ownership and use' in NSP. In this projection, although the electricity demand per household shows a clear decrease, the electricity demand per person barely decreases (households with less 'Appliances ownership and use' points comprise mostly smaller households with rather "normal punctuation per person" (normal amounts and use of appliances per person) and some larger households with "low punctuation per person" (small amounts and use of appliances per person), therefore the decrease in electricity demand per person is small). This happens despite the characteristics of the indicator specify a clear decrease in the use of appliances in the scenario.

For this reason, the aggregates have only been obtained for the energy demand per household. Therefore, in the same way that the number of households are used to obtain the energy demand of the whole population in each scenario, the scenario household sizes found in Table 6.5.1.2 are used to obtain the energy demand per person.

7.2 Managing the projections

To manage the projections and obtain the aggregates, MATLAB was again used. In this case, only one function was developed to obtain the aggregates of particular projections and plot them (it produces the aggregates but it does not format the results in an easy-to-understand layout). As the number of aggregates needed is low, the format of the results and further plots were obtained *ad hoc* instead of preparing any extra function or script. The function is reviewed below:

aggregates.m: function that aggregates projections obtained with *projectall.m* for a particular scenario and type of day. The inputs it needs are: a cell with all the results obtained with *projectall.m*; a vector with the variables' numbers in order (the numbers corresponding to the variable's row in the outcome of *projectall.m*); a vector with the relative weight for each projection in the same order as the variables; a variable signalling if the aggregate is for Edata or Gdata; the name of the scenario for which the aggregate is sought; the season to be aggregated; and the type of the day for which the aggregate is sought. The function multiplies each projection by its weight and adds them all up. Then it divides it by the sum of the weights. Therefore, the weights introduced do not need to be normalised (*i.e.* that their sum equals one). The function produces as an output: a matrix with the daily energy averages per household and per person of all the projections aggregated, the average daily energy demand resulting from the aggregation (also per household and person), and these values for the base; a matrix with the daily profiles per household of the projections aggregated, the aggregate, and the base; and a matrix with the daily profiles per person of the projections aggregated, the aggregate, and the base. The function also produces a plot showing all the projections, the aggregate and the base.

Find this file within the electronic data provided with this thesis (see Appendix D).

7.3 Aggregates

In this section two sets of aggregates with all projections are presented for Edata and Gdata in each scenario, one set unweighted (same weight for all projections) and one set weighted. The weights of the weighted aggregates attempt to take into account the dependencies between variables and their relative importance on the energy demand of households in each scenario. Once the aggregates are found, the total energy demand in the scenario and the energy demand per person are calculated; the former with the number of household in the scenario, and the latter with the scenario household size.

As it is impossible to find a set of independent variables that cater all the determinants of household energy demand, some of the variables are not independent from each other.

This fact introduces redundancies in the projections (the statistical double counting problem for which, in this case, two or more projections partially introduce the same behaviour in the aggregate (Nardo et al., 2005)).

For example, let A, B and C be three variables determining the energy demand of households. If they are independent from each other, their projections will account for distinct independent household energy demand behaviours. If these projections are then averaged (each one has a weight of, say, 1), the aggregate will have an equal contribution of each variable. But, what happens to the aggregate if A and B are the same variable with a different name (let's call it variable AB)? In this case, the aggregate is much closer to the behaviour of the variable AB than to the behaviour of the variable C. This is because the projection of variable AB has a weight of 2 (the projection of A is equal to the projection of B and both have a weight of 1) while the projection of variable C has a weight of 1. In this case, if the weights of the projections of A and B are divided by 2, their combined weight equals 1. Then, the aggregate has an equal contribution of the variables C and AB. This example shows the case of two totally dependent variables; when the number of totally dependent variables is n, in order to account for these dependencies their weights have to be divided by n.

In general, variables are not 100% dependent of each other (they would be the same variable!), but in some cases there are clear degrees of dependency. It is valuable to take these dependencies into account to ensure aggregates are not biased by projections which convey overlapping behaviours. The weighted aggregates can take them into account. However, the weights also need to take other aspects of the variables and scenarios into account; different scenarios are usually driven by distinct variables and in different degrees. Therefore, some criteria are needed to define the weights.

The criteria used here to define the weights are: (1) give a general weight to each variable accounting for their importance determining the electricity or gas demanded by households (different variables affect the energy demand of the households with different magnitudes), (2) account for dependencies between particular variables by decreasing their general weights with a factor representing their degree of dependency, and (3) determine the variables which mostly drive the behaviour in the scenario and increase their weight accordingly. The development of these criteria follows:

(1) General weights: The general weights which account for the importance of each projection for the household electricity and gas demands are shown in the rows marked with (1) in Table 7.3.0.1.

(2) Dependent variables: There are two groups of variables which are directly correlated[2]:

[2]Clearly, the dependencies between the variables projected are intricate and may have many subtle effects. However, accounting for such underlying effects is out of the scope of this thesis and, as will be seen further in this chapter, small changes in the weights do not alter the aggregates substantially.

- The first group contains 'Percentage of children in the household', 'Household size' and 'Number of bedrooms'. Households with a larger percentage of children tend to be larger. At the same time, the size of the household tends to be correlated with the number of bedrooms the dwelling has. As the degree of dependency of these three variables is not very high, it can be considered that their total weight should be that of two variables (while they are three variables). Therefore, their weights are normalised to 2 by multiplying them by 2/3.
- The second group affects only the electricity demand, and contains 'Attitudes to energy efficiency and sustainability' and 'Appliances ownership and use'. The use of appliances is mostly driven by the population's attitudes to sustainability, but not completely. Therefore, the weight of these projections has to be slightly larger than that of a single projection. As seen before, in order to make the weight of two variables be that of a single one, their weights have to be divided by 2. As in this case the combined weight has to be slightly larger than that of a single variable, their weight is divided by 1.7.

(3) Driving variables for each scenario: In the case of NSP, this is the 'Attitudes to energy efficiency and sustainability', since the main driver of this scenario is the change in the values of the population. This is a very important driver, therefore it is increased by 60%. The driving variables for PR are 'Energy efficiency of appliances' and 'Energy efficiency of dwellings' for the electricity and gas respectively. These are also clear drivers but less than that of NSP, because they are only consequences of the measures taken by the government. Therefore, they are increased by 50%. In MF the driving variable is again 'Attitudes to energy efficiency and sustainability', since the main change is that these worsen. However, it is not as a stark change in these attitudes as in NSP, therefore it is only increased by 40%. FW has as driving variable 'Energy purchasing power' because the capacity of FWp to use energy is its main driver. In this case this variable is also a very powerful driver, therefore it is increased by 60%.

A review of the weights resulting by applying each criteria (in order) for each projection in each scenario can be found in Table 7.3.0.1. The weights shown in criterion (3) are then the final weights for each projection used to calculate the weighted aggregates in each scenario. The exact values given to these weights are subjective in nature. However, the process of deriving them is transparent and driven by the importance of the different variables in the household energy demand, their dependencies and the interpretation of the scenario narratives.

With these weights all the aggregates can be found. Figures 7.3.0.1, 7.3.0.2, 7.3.0.3, 7.3.0.4 show the projections and resulting aggregates (average and weighted) for the electricity demand per household in NSP, PR, MF and FW respectively. The weights shown beside the variable name are the final weights that appear in Table 7.3.0.1 but normalised (their sum equals 1). Table 7.3.0.2 shows the aggregates of the daily electricity and gas averages per household for each scenario, together with the projections per household that were aggregated, and the values of the bases. And Figures 7.3.0.5, 7.3.0.6, 7.3.0.7, 7.3.0.8 show the projections and resulting aggregates for the gas demand per household in NSP, PR, MF and FW respectively.

Table 7.3.0.1: Weights defined following the three criteria for each projection and scenarios.

Criteria	Energy efficiency of appliances	Attitudes to energy efficiency and sustainability	Energy efficiency of dwellings	Percentage of children in the household	Energy purchasing power	Space heating	Type of building	Number of bedrooms	Appliances ownership and use	Energy poverty	Household size
Electricity											
(1)	2.00	2.00	–	1.00	1.00	3.00	1.00	1.00	2.00	1.00	1.00
(2)	2.00	1.18	–	0.67	1.00	3.00	1.00	0.67	1.18	1.00	0.67
(3) NSP	2.00	1.88	–	0.67	1.00	3.00	1.00	0.67	1.18	1.00	0.67
(3) PR	3.00	1.18	–	0.67	1.00	3.00	1.00	0.67	1.18	1.00	0.67
(3) MF	2.00	1.65	–	0.67	1.00	3.00	1.00	0.67	1.18	1.00	0.67
(3) FW	2.00	1.18	–	0.67	1.60	3.00	1.00	0.67	1.18	1.00	0.67
Gas											
(1)	–	2.00	2.00	1.00	1.00	–	2.00	2.00	–	1.00	2.00
(2)	–	2.00	2.00	0.67	1.00	–	2.00	1.33	–	1.00	1.33
(3) NSP	–	3.20	2.00	0.67	1.00	–	2.00	1.33	–	1.00	1.33
(3) PR	–	2.00	3.00	0.67	1.00	–	2.00	1.33	–	1.00	1.33
(3) MF	–	2.80	2.00	0.67	1.00	–	2.00	1.33	–	1.00	1.33
(3) FW	–	2.00	2.00	0.67	1.60	–	2.00	1.33	–	1.00	1.33

Criterion (1) General weights. Criterion (2) Dependent variables. Criterion (3) Driving variables for each scenario.
Weights in criterion (3) are the final weights used for the aggregates (the weights shown in the figures are these same weights but normalised).

Figures 7.3.0.9 and 7.3.0.10 show the unweighted aggregates obtained for each future scenario with the base shown as benchmark for electricity and gas demand per household respectively, and Figures 7.3.0.11 and 7.3.0.12 show the same but for the weighted aggregates.

With the values of the of the household electricity and gas demands from Table 7.3.0.2, the number of households and average household size of each scenario, total and per person energy demands can be found. Table 7.3.0.3 shows these values for electricity and gas, as well as for the sum of both energy sources. In the case of gas, the energy demand per person is shown, both for the whole scenario population, and for those who use gas only. It also shows, for each scenario, the household size, the number of households and the

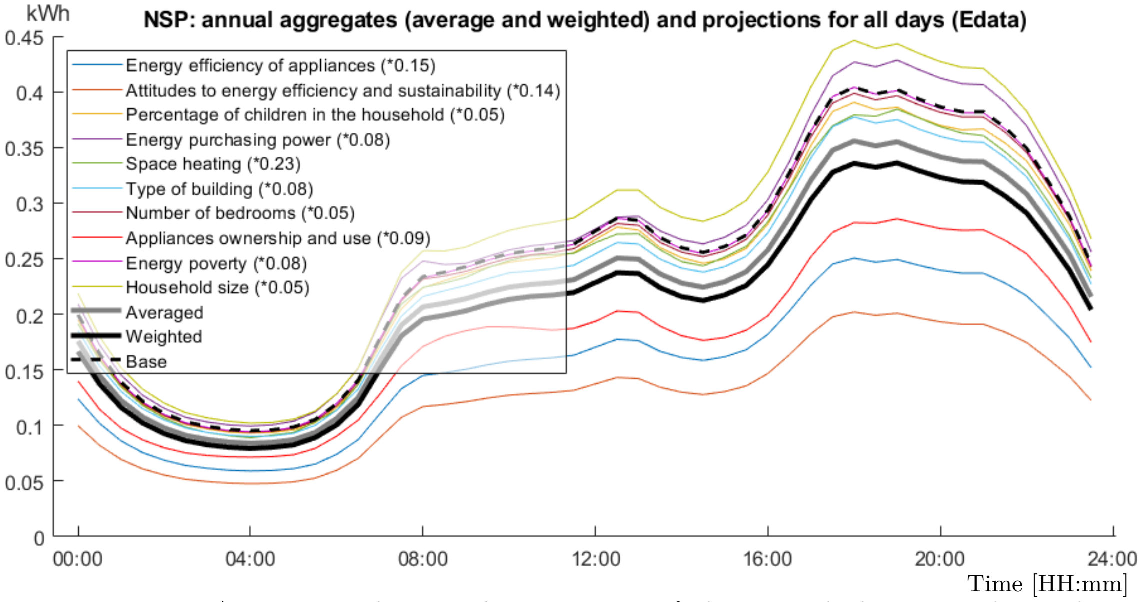


Figure 7.3.0.1: Aggregates, base and projections of the annual electricity demand per household for NSP. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

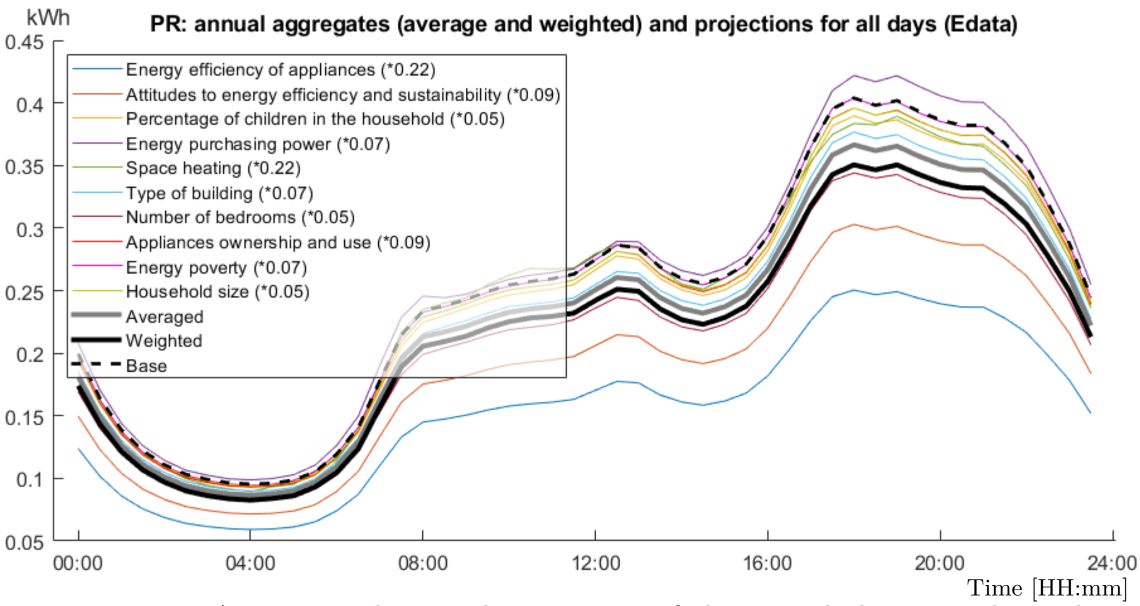


Figure 7.3.0.2: Aggregates, base and projections of the annual electricity demand per household for PR. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

fraction of households using gas, which are the values needed to find the total and per person energies.

Table 7.3.0.4 shows the resulting evolutions of the household energy demand in each scenario found with the results of Table 7.3.0.3. These evolutions can now be applied to the energy demand of UK to obtain an approximation to the different behaviours the household energy demand can show in the future and aid the decision-makers in finding resilient solutions.

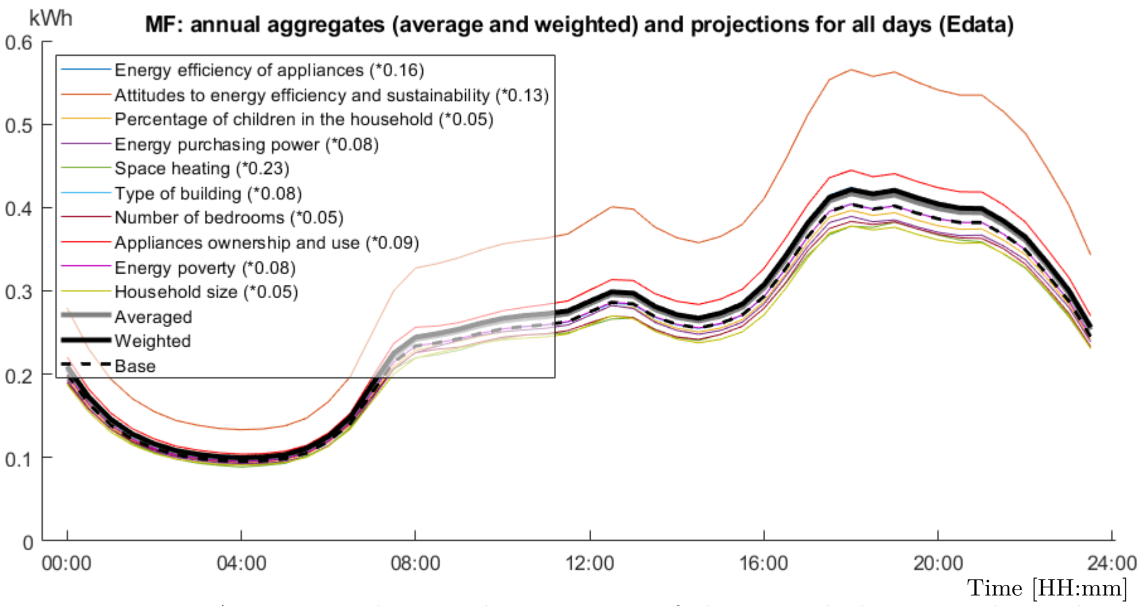


Figure 7.3.0.3: Aggregates, base and projections of the annual electricity demand per household for MF. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

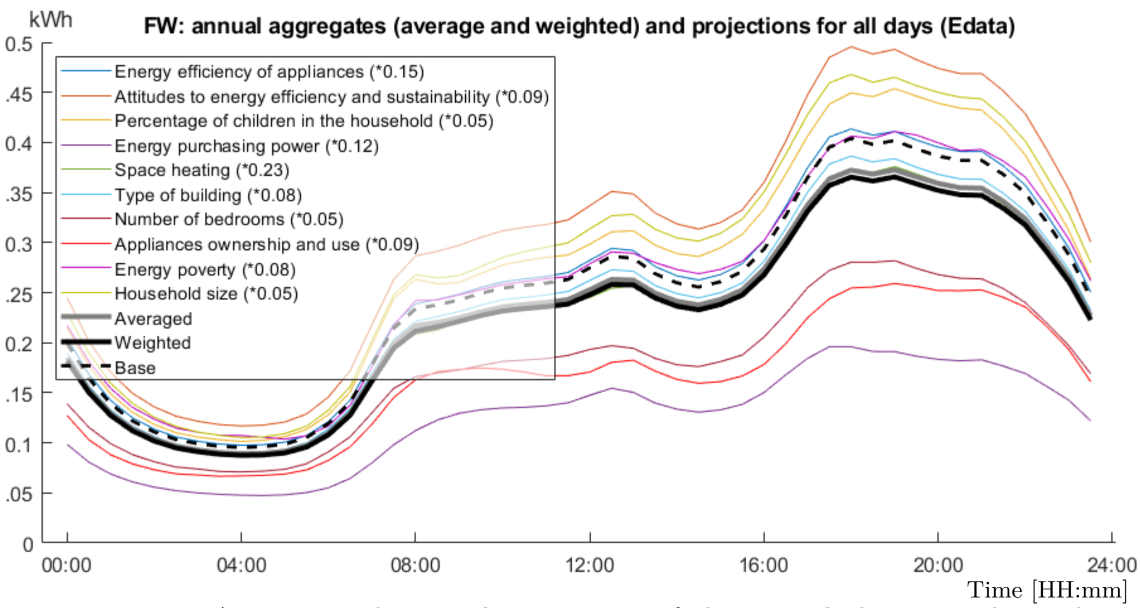


Figure 7.3.0.4: Aggregates, base and projections of the annual electricity demand per household for FW. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

7.4 Analysis, comparison and discussion of the aggregates

In this section the unweighted and weighted aggregates are analysed, the differences between them are discussed, and an analysis of the results obtained for the total and per person energy demands in the different scenarios is performed.

A feature which is very apparent when analysing the aggregates is that the differences between the unweighted and the weighted averages are not large —the difference between

Table 7.3.0.2: Resulting aggregates for each future scenario.

(kWh)	Average (equal weights)	Weighted aggregate	Energy efficiency of appliances	Attitudes to energy efficiency and sustainability	Energy efficiency of dwellings	Percentage of children in the household	Energy purchasing power	Space heating	Type of building	Number of bedrooms	Appliances ownership and use	Energy poverty	Household size
Edata (11.94)													
NSP	10.52	9.96	7.40	5.97	–	11.53	12.45	11.41	11.12	11.77	8.54	11.90	13.09
PR	10.86	10.43	7.40	8.95	–	11.53	12.36	11.72	11.12	10.20	11.69	11.90	11.71
MF	12.35	12.49	12.53	16.71	–	11.73	11.58	11.29	11.93	11.43	13.11	11.94	11.21
FW	11.06	10.85	12.22	14.64	–	13.20	5.95	10.98	11.38	8.38	7.78	12.34	13.73
Gdata (21.66)													
NSP	19.17	17.42	–	10.83	14.08	21.67	21.60	–	19.70	21.37	–	21.68	22.44
PR	19.49	18.51	–	16.24	15.16	21.62	21.70	–	19.78	18.17	–	21.68	21.56
MF	22.38	23.31	–	30.32	20.58	21.62	21.18	–	22.02	20.42	–	21.66	21.21
FW	20.27	20.35	–	27.56	20.50	22.07	9.10	–	21.12	17.47	–	21.77	22.57

All projections (which do not involve a change in the scenario's population) obtained were aggregated. The values for the base are also shown between brackets beside the data name.

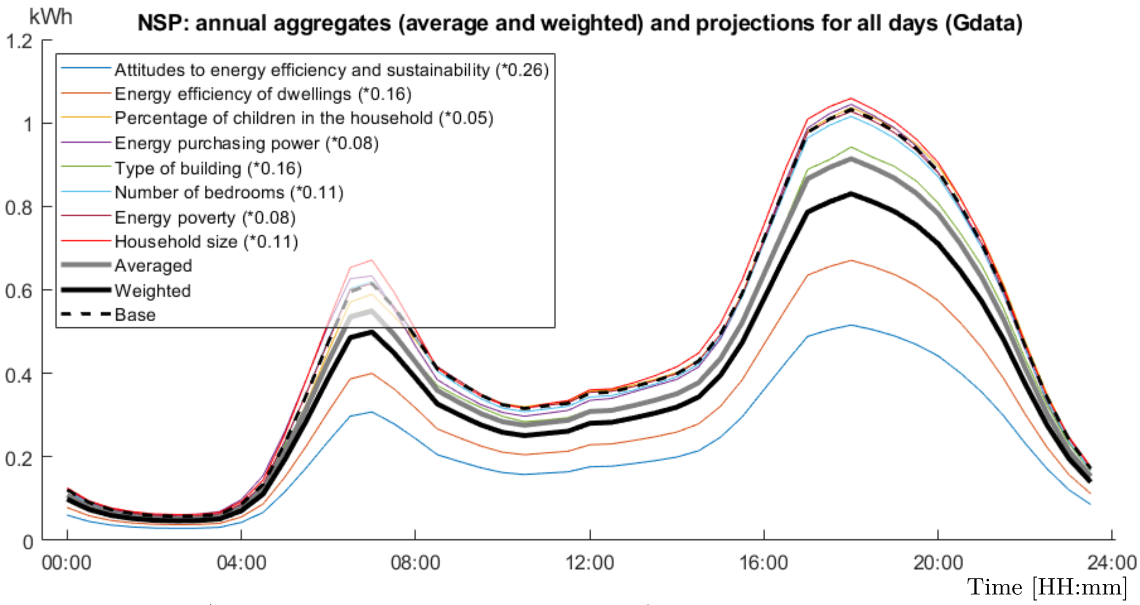


Figure 7.3.0.5: Aggregates, base and projections of the annual gas demand per household for NSP. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

those of the gas demand in NSP being the largest, and those of the electricity demand in MF and FW are almost non-existent—. These small differences are larger for the gas demand than for the electricity demand.

It is also apparent that the weighted aggregates are all more distant from the base than the averages, *i.e.* their characteristics are more distinct. This is because the weights mostly

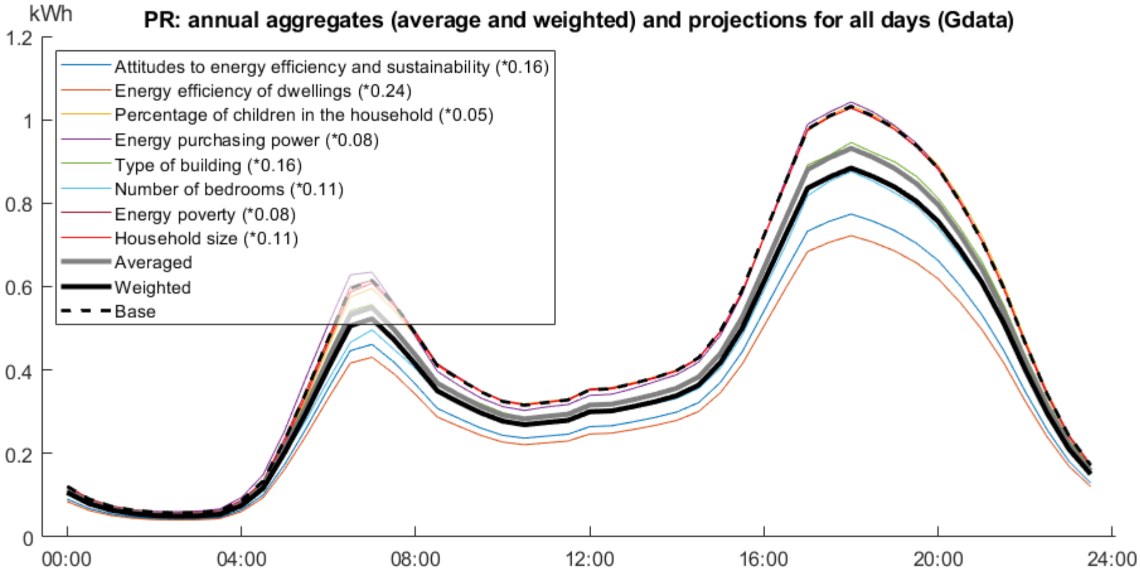


Figure 7.3.0.6: Aggregates, base and projections of the annual gas demand per household for PR. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

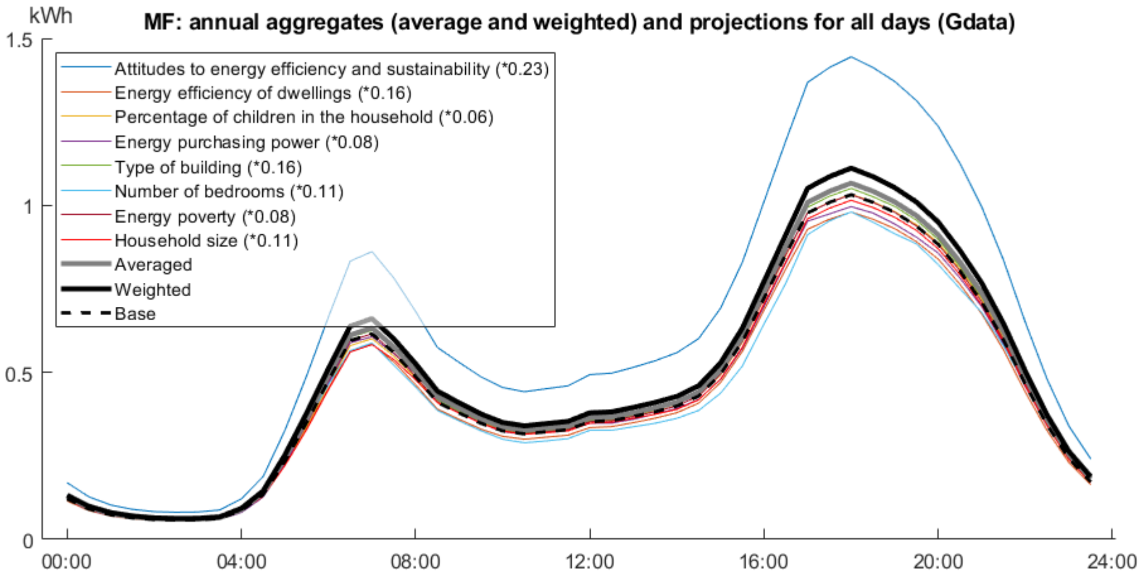


Figure 7.3.0.7: Aggregates, base and projections of the annual gas demand per household for MF. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

emphasise those projections which follow the driving characteristics of each scenario, which are the ones which mostly contributed to their deviation from the base in the first place.

The fact that the differences between weighted and unweighted aggregates are small is satisfying and indicates that the resulting aggregates are robust. This is because these differences are small even though the range of weights is large; the largest weight is 4.8 times larger than the smallest weight (as the weights are normalised, their absolute value is irrelevant).

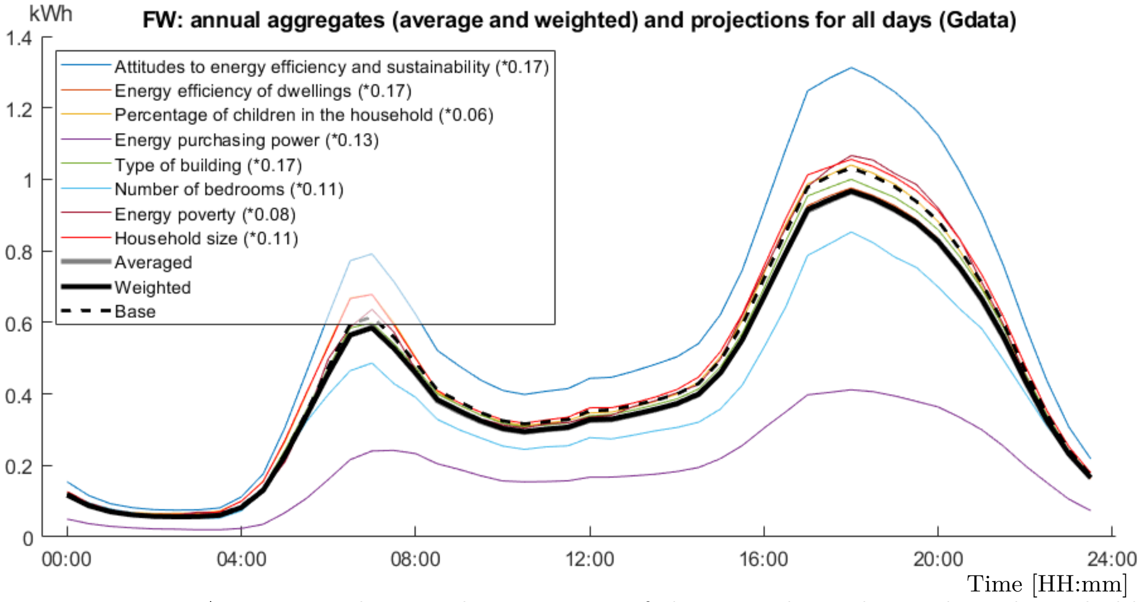


Figure 7.3.0.8: Aggregates, base and projections of the annual gas demand per household for MF. The weight applied to each projection for the weighted aggregate is shown between brackets after their name in the legend.

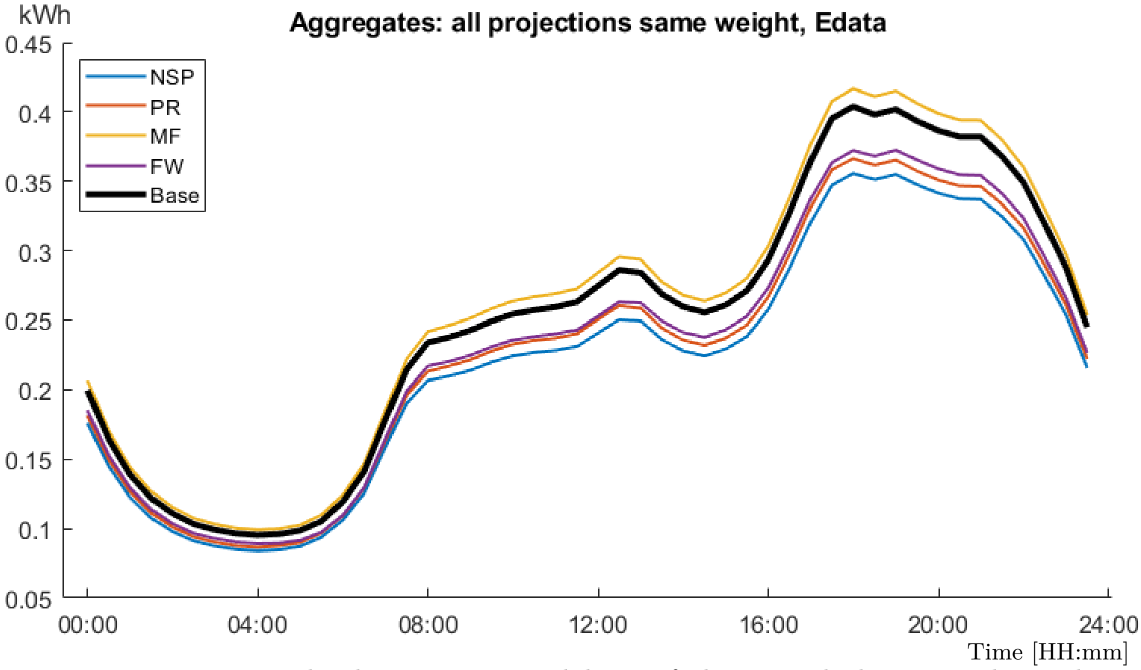


Figure 7.3.0.9: Unweighted aggregates and base of the annual electricity demand per household for all scenarios.

However, these small differences are partly due to the number of projections aggregated; for weights of similar relative value, the more projections are aggregated the smaller the difference between the unweighted average and the weighted average. It is important to emphasise here that a larger amount of projections aggregated does not necessarily make the aggregate better, *i.e.* more informative. In general, when projections following the behaviour of irrelevant variables are added to the aggregates —*i.e.* variables which are not significant determining the energy demand of households—, the only effect these

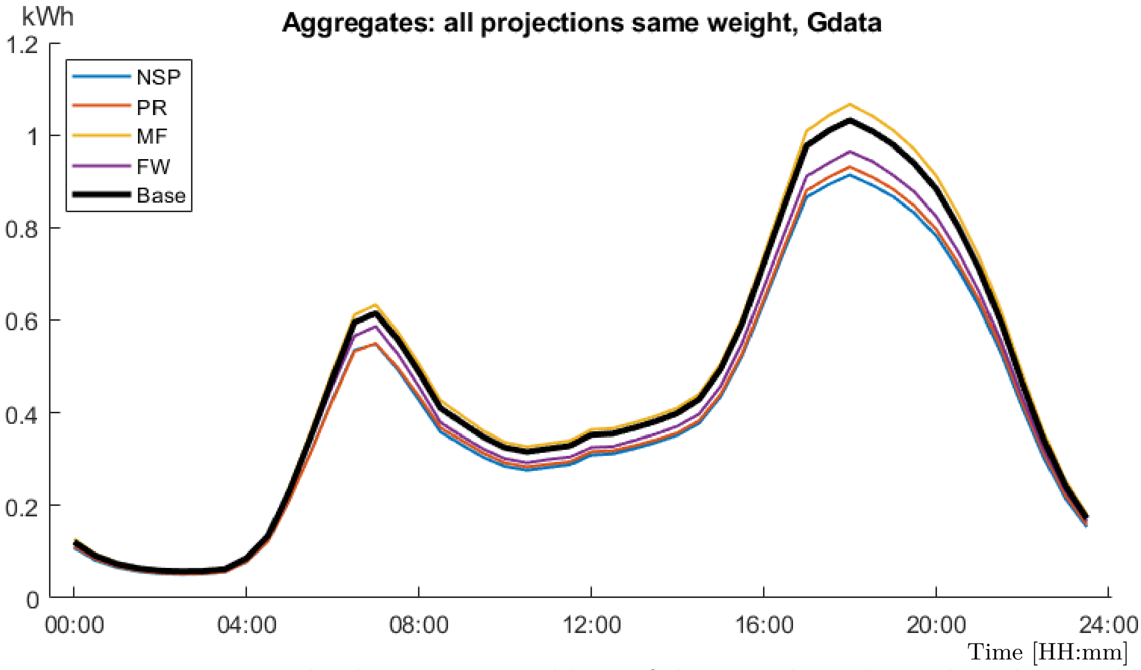


Figure 7.3.0.10: Unweighted aggregates and base of the annual gas demand per household for all scenarios.

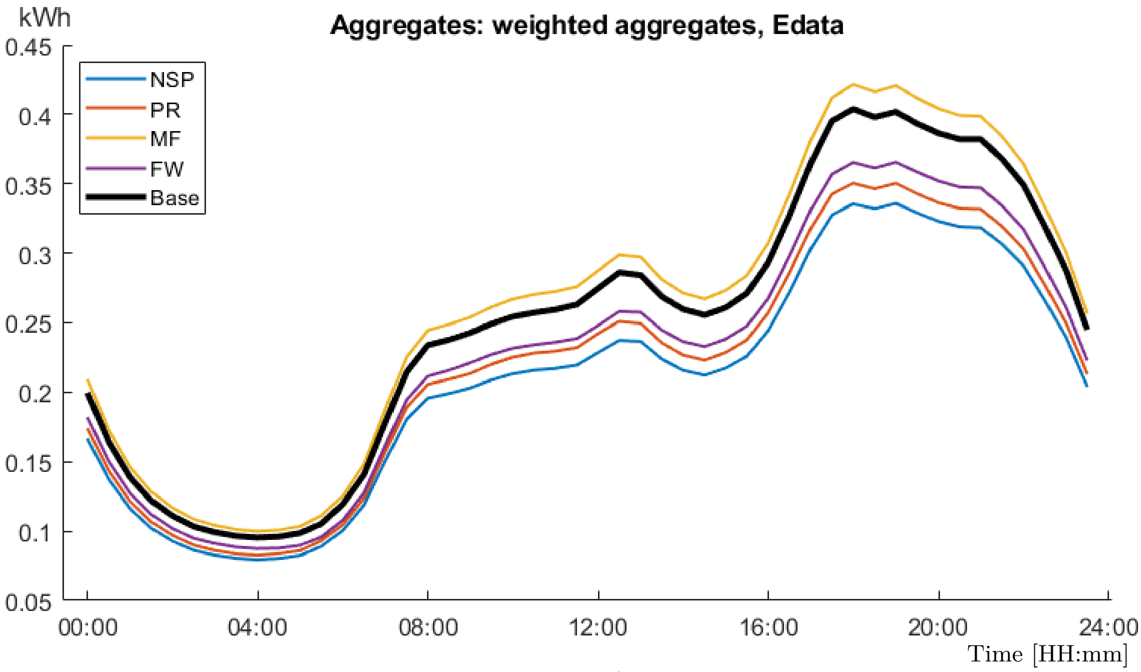


Figure 7.3.0.11: Weighted aggregates and base of the annual electricity demand per household for all scenarios.

have is to make the aggregate more similar to the base. This is because the groups of households defined to obtain the projection will normally not show differences in their energy demand (if a variable is not a determinant of the energy demand in households, different groups with a constant "value" of this variable will not, in principle, demand different amounts of energy, and their energy demand will be very similar to that of the base). And, in the case they do show substantial differences in their energy demand, these

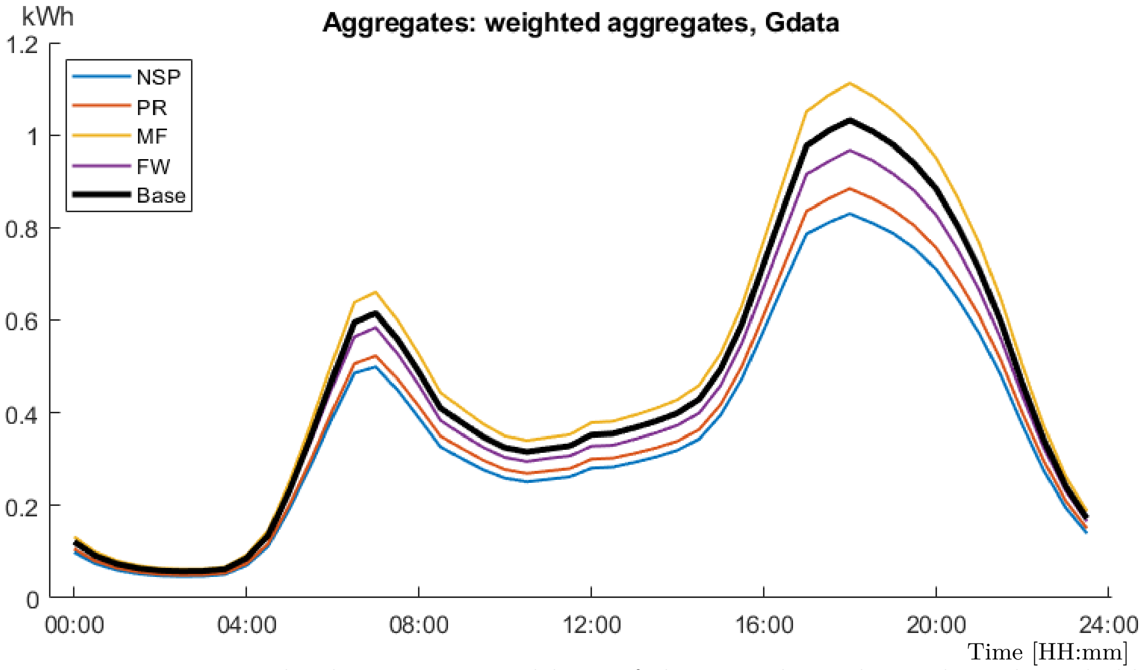


Figure 7.3.0.12: Weighted aggregates and base of the annual gas demand per household for all scenarios.

differences will not be due to the variations in the specific variable projected (it is not a relevant variable) but to chance or a correlation with another variable. Including such a projection would make the aggregate less informative.

For example, if an irrelevant variable like 'Number of brooms in the dwelling' would be projected, the energy demand behaviour of the households group with one broom would, in principle, not differ from the energy demand behaviour of the households group with two brooms, nor would it be different than that of the base. And, if their behaviour is substantially different, it would only be because of some hidden correlation between the number of brooms in the dwelling and another variable which actually is a determinant of the household energy demand —although households with no brooms may be so dusty that they need to spend more in lighting to keep comfortable light levels—, or by chance. In both cases, introducing such a projection would increase the uncertainty in the aggregate instead of decreasing it, making it less informative.

Here it is important to recall that when a scenario is heavily shaped by one specific (group of) variable(s), the projections of other variables portray effects of very secondary order. Therefore, an aggregate made up of few but key projections may also be more informative than an aggregate comprised of many projections which give information of secondary order.

In addition, the decision of which variables to aggregate and, to a small extent, the weights given will depend on the question that one wants to answer —and on which projections are available to aggregate—. Each projection gives a particular bit of information. Therefore, the aim of the aggregates and the information conveyed by each projection must be clear before obtaining any aggregate if they are to be useful.

Table 7.3.0.3: Aggregated total energy demand, energy demand per household and energy demand per person for each scenario.

	Unweighted aggregates				
(kWh)	NSP	PR	MF	FW	Data
Electricity per household	10.52	10.86	12.35	11.06	11.94
Electricity per person	3.01	4.94	6.86	2.70	4.98
Total electricity demand	165.16 M	301.91 M	419.90 M	171.43 M	308.05 M
Gas per household (gas users)	19.17	19.49	22.38	20.27	21.66
Gas per person (gas users)	5.48	8.86	12.43	4.94	9.03
Gas per person (whole population)	0.27	1.68	10.69	1.31	7.31
Total gas demand	15.05 M	102.95 M	654.39 M	83.07 M	452.65 M
Total energy per household	11.48	14.56	31.60	16.42	29.48
Total energy per person	3.28	6.62	17.55	4.00	12.29
Total energy demand	180.21 M	404.85 M	1074.29 M	254.50 M	760.70 M
	Weighted aggregates				
Electricity per household	9.96	10.43	12.49	10.85	11.94
Electricity per person	2.85	4.74	6.94	2.65	4.98
Total electricity demand	156.37 M	289.95 M	424.66 M	168.18 M	308.05 M
Gas per household (gas users)	17.42	18.51	23.31	20.35	21.66
Gas per person (gas users)	4.98	8.41	12.95	4.96	9.03
Gas per person (whole population)	0.25	1.60	11.14	1.31	7.31
Total gas demand	13.67 M	97.77 M	681.58 M	83.40 M	452.65
Total energy per household	10.83	13.95	32.54	16.23	29.48
Total energy per person	3.09	6.34	18.08	3.96	12.29
Total energy demand	170.05 M	387.72 M	1106.24 M	251.57 M	760.70
Household size (persons)	3.50	2.20	1.80	4.10	2.40
Fraction of households using gas	0.05	0.19	0.86	0.26	0.81
Number of households	15.70 M	27.80 M	34.00 M	15.50 M	25.80 M

M stands for million.
The lower part of the table shows the values needed for the calculations: Household size and Number of households from Table 6.5.1.2, and Fraction of households using gas from Table 6.5.7.5 (the fraction for the whole FW is calculated using the weights for FWr and FWp from Table 6.1.0.2 —0.28·FWr; 0.72·FWp—). The values for the column Data are obtained with the energy demand per household from the data samples and the values for Household size, Number of households and the Fraction of households using gas from the base scenario of DRC.

All this shows that, on the one hand, one has to be careful in the whole process of projecting data and producing aggregates, *i.e.* it is very important to accurately: (a) define the variables and groups that are going to be projected so that they are relevant, adequate and cater for the domain of study, (b) derive the factors (corrections or ratios) so that they reflect the characteristics of the scenarios, and (c) derive the weights of the projections to account for their dependencies and importance in forming the aggregate. However, on the other hand, small differences in some of these steps do not introduce significant differences in the resulting aggregates. Therefore, if the process is done with care, and the information conveyed by each projection and that sought with the aggregates are clear, the results will be robust and informative.

Comparing the plots showing aggregates, one can see that the aggregates which differ the most from the base are those of NSP followed by those of PR and FW. All these aggregates show a decrease in the energy demand. The aggregates of MF are very similar to the base (their only outlier projection is 'Attitudes to energy efficiency and sustainability),

Table 7.3.0.4: Resulting evolution relative to the base of the daily household energy demands in each scenario found with each aggregate.

Unweighted aggregates				
(% of change)	NSP	PR	MF	FW
Electricity per household	−11.89	−9.05	3.43	−7.37
Electricity per person	−39.58	−0.78	37.91	−45.78
Total electricity demand	−46.38	−1.99	36.31	−44.35
Gas per household (gas users)	−11.50	−10.02	3.32	−6.42
Gas per person (gas users)	−39.31	−1.84	37.77	−45.22
Gas per person (whole population)	−96.25	−76.97	46.27	−82.12
Total gas demand	−96.68	−77.26	44.57	−81.65
Total energy per household	−61.07	−50.61	7.16	−44.31
Total energy per person	−73.30	−46.12	42.88	−67.40
Total energy demand	−76.31	−46.78	41.22	−66.54
Weighted aggregates				
Electricity per household	−16.58	−12.65	4.61	−9.13
Electricity per person	−42.80	−4.71	39.48	−46.81
Total electricity demand	−49.24	−5.87	37.85	−45.41
Gas per household (gas users)	−19.58	−14.54	7.62	−6.05
Gas per person (gas users)	−44.85	−6.77	43.49	−45.00
Gas per person (whole population)	−96.60	−78.13	52.35	−82.05
Total gas demand	−96.98	−78.40	50.58	−81.58
Total energy per household	−63.27	−52.70	10.35	−44.95
Total energy per person	−74.81	−48.40	47.13	−67.78
Total energy demand	−77.65	−49.03	45.42	−66.93

The evolutions presented in this table are the percentage of change that the energy demands found with the aggregates show in respect to those found with the data —last column in Table 7.3.0.3—. Note that (a) the weights used for the weighted aggregates are those presented in Criterion (3) of Table 7.3.0.1, (b) the unweighted aggregates give each projection the same weight, (c) the factors and groups of households used in each projection are those presented in Tables 6.5.0.1 and 6.5.0.2 (pages 107 and 109), and (d) it was not possible to project two important variables: 'Time spent at home' and 'Microgeneration'.

and it is the only one which shows an increase in energy demand. MF is the most "business as usual" scenario; therefore, it is satisfying that the dispersion of its projections is the lowest, as this means that the behaviours do not change substantially in comparison to the current.

It is also clear that, within a single scenario, the projections for electricity demand are much more variable than those for gas demand. This indicates that the differences in gas demand between the groups defined for the different variables are not large, which may suggest that they could be better defined. However, one has to take into account that the variable which most affects the amount of gas demanded is 'Space heating'. This variable was not projected because what it does is to change the household population using gas but is taken into account when calculating the total gas demand in the scenarios. Therefore, its effects are not shown in the aggregates but are taken into account when calculating the gas demand of the whole population in the scenarios.

A variable that would, in principle, significantly affect gas demand —and to a lesser degree, electricity demand as well— is a variable describing the temperature at which the dwelling is held. However, such a variable is difficult to define (the temperature may vary in time, different rooms may be kept at different temperatures, it may depend on who occupies each room at each point in time...), it is difficult to measure (the previous uncertainties make it difficult to obtain reliable measures unless data could be obtained directly from thermostats), and it may be taken into account within 'Attitudes to energy efficiency and sustainability'. For these same reasons no specific indicator to convey this information was developed to complement the DRC scenarios. Therefore, the analysis to develop the values of the corrections for 'Attitudes to energy efficiency and sustainability' could have been deeper and explicitly account for this effect. However, such a detailed analysis is out of the scope of this thesis; the aim is not to obtain the most accurate "result" possible, but to demonstrate the use of the tool.

Table 7.3.0.3 shows the full picture of the energy demand in each scenario obtained from the aggregates. It also shows the values resulting using the energy demand per person from the data samples. And Table 7.3.0.4 shows the evolutions the aggregated energy demands represent in respect to those from the data samples. The values obtained show much lower variation between aggregates (unweighted vs weighted aggregates) than within aggregates (scenario vs scenario). This fact supports the conclusion that, in general, small random differences in the weights given to the different projections, in the factors derived for the groups and/or in the exact definitions of the variables and their groups do not introduce significant differences in the resulting aggregates. What is important is the accumulation of methodical differences accentuating the scenarios' characteristics in these factors and definitions. Therefore, although isolated inaccuracies, imprecisions or differences in judgement do not significantly affect the resulting aggregates, an accumulation of them may actually do, especially if their effects are not randomly distributed. This is why the work needed to obtain the aggregates cannot be taken lightly.

In addition, there are variables which disproportionally drive the results for each scenario because they affect the aggregates as a whole instead of affecting a single projection: the total population and the household size of the scenarios, as well as the fraction of households using gas for the gas demand. This is because, unlike the other variables (for which any inaccuracy in the definition affects their projection but its influence in the aggregates is reduced by the aggregation of other projections), they affect the whole aggregate. Therefore, any misjudgement in these variables affects the conjunction of all projections. This means that one has to exercise great care deriving these values in order to obtain a meaningful picture of the total and per person energy demands in each scenario.

Continuing with Tables 7.3.0.3 and 7.3.0.4, they show stark differences in the total energy demanded in the scenarios, and in comparison to that obtained with the data. The differences are especially large for gas, since in some scenarios its use decreases a lot. For example, in NSP the proportion of households using gas is really small (5%, see Table 7.3.0.3), which leads to a difference with the gas demand in MF of more than 40 times for the unweighted aggregate and of almost 50 times for the weighted aggregate. The difference in the gas demands per household which use gas are, however, much lower although still significant. It is also significant that MF is the only scenario where the total use of gas is somewhat similar to the current, although significantly larger. This is because in the other scenarios the percentage of households using gas decreases significantly, decreasing the total gas demand. In addition, in NSP and FW the average demand per person within gas users also decreases considerably.

The differences in the electricity demand are also considerable; the ratio in total electricity demand between NSP and MF is larger than 2.5 times for both unweighted and weighted aggregates. MF is the only scenario where the total electricity demand increases, and it does so substantially (it is around 37% —1.4 times— larger than the base). In PR the total electricity demand remains roughly constant while in NSP and FW it almost halves. The electricity demand per household shows the expected behaviour explained above (NSP<PR<FW<base<MF). However, the effect of the average household sizes makes FW the scenario with the lowest electricity demand per person. Although the electricity demands per household of NSP and PR are similar, the fact that NSP has a smaller population which tend to live in larger households, makes its total electricity demand and electricity demand per person show large differences when compared to PR. And the total electricity demand of PR is very similar to that found using Edata.

Finally, although electricity and gas are used in different ways and these are not the only energy sources used in households —*e.g.* microgeneration (which, unfortunately, was not possible to project) is increased in all scenarios, in NSP and MF there is a significant use of district heating and co-generation, and in FW the use of biomass for heating and cooking purposes is widespread—, they are the largest sources of household energy. Therefore, it is also interesting to compare the total amounts of electricity plus gas demanded by the households of each scenario.

As it is logical from the previous analysis, these results show a huge disparity which is the result of adding up the already disparate demands of electricity and gas. The total energy demand and the energy demand per person in MF, which are the only ones larger than those obtained with the data samples, are around 6 times larger than those of NSP, which are less than half of those in PR. The energy demands of FW are between these last two. These differences are very substantial.

In summary, the process of giving the projections weights improves the aggregates by decreasing the effect of redundant behaviours, and by adjusting the influence each projection exerts in the aggregate to the degree in which each variable determines household energy demand and their importance in the scenarios. The redundant behaviours come from the fact that some variables are not independent from each other. It is clear that the dependencies between variables are intricate and subtle. Finding all the dependencies between variables and quantifying them in order to define weights could be an enormous task. However, as shown above, the effects the weights have on the aggregates are limited. The changes in the weights that would take into account subtle dependencies would be small. Therefore, although it is important that the weights account for clear dependencies between variables, it is also not needed that they account for more indirect ones.

7.4.1 Improving planning for UK household energy demand

This subsection presents brief examples of how the evolutions shown in Table 7.3.0.4 can improve the planning of the future infrastructures providing households with energy. The purpose of these examples is to showcase the use of the tool and the evolutions found with it; a deep analysis is outside the scope of this thesis.

By applying the changes in behaviour (evolutions) shown in Table 7.3.0.4 to current UK energy demand (electricity, gas or both), one can obtain an estimate of the different evolutions the energy demand in UK may take. These give a benchmark that decision-makers could use to improve the planning of the future energy systems in the UK. The evolutions shown in that table are those found for the daily energy demands. However, the evolutions of each of the half an hour periods comprising the energy profiles could be found as well in order obtain the evolution of the daily energy profiles.

These evolutions show a clear general trend to lower energy (electricity and gas) demands. Only in MF there is a significant increase that affects both, electricity and gas demands (of around 37% and 50% respectively). This suggests that an investment to increase the capacity of the electric or gas energy distribution networks further than these increases is not needed in any of the futures studied here and, therefore, likely to be a waste of money and resources. In addition, any plan to increase the capacity of these networks would be rendered useless if the future of UK differs from MF. The same is true for any plan to decrease the capacity of these networks if the future of UK resembles MF. Therefore, it might be advisable to prepare the energy networks to be flexible so that they can be gradually adjusted to any of the scenarios; any solution which makes them more flexible is going to be more resilient than a rigid solution.

If, in addition, one takes into account the variable 'Microgeneration' —which was not possible to project—, one sees that the households of all scenarios show an increase in the use of microgeneration (although in FW only by the rich). This suggests that the electricity demand will, in general, be lower than that indicated by the aggregates. In addition, it also suggests that it will be, to a large extent, dependent on on weather conditions, with periods where the network will need to absorb the excess of energy produced in the dwellings. Therefore, investing to make the electricity distribution networks bi-directional and implementing systems to give use to this excess of electricity generated could pay off.

Likewise, one can do similar analyses for the evolution of the energy demand per person and per household, or imagine more daring proposals arising from the analysis of the total energy demands. For example, in most of the scenarios (NSP, PR and FW) the demand for gas decreases dramatically. One could consider the possibility, at least for the case of the two sustainable scenarios (NSP and PR), to stimulate the complete extinction of gas as household energy source and adapt its infrastructure to distribute hydrogen (Melaina et al., 2013). This hydrogen could be produced with the excess of energy produced in sunny and windy days and be used when there would be a lack of them. For such a measure to be possible, many technical issues must be studied in advance (*e.g.* the gas infrastructure should be adaptable to distribute hydrogen —see Melaina et al. (2013)—). Therefore, the study of these issues to investigate the feasibility of such project could be triggered by the analysis of the aggregates obtained here.

These are just some examples of the applications the aggregates could have improving decision-making. They show how the aggregates may be useful to improve the planning of the household energy systems. However, when using these aggregates, one has to remember that almost half of the population of FW live in informal settlements —meaning that the evolutions found for this scenario represent the upper limit of their energy demands— and that they portray only part of the picture. To have a complete picture of the energy demanded by households one has to include, at least, district heating, co-generation and biomass in the relevant scenarios, and take into account the characteristics of the variables which could not be projected.

7.4.2 Comparing aggregates to DRC

As DRC contains an indicator called 'Domestic energy demand', it is a good exercise to compare the evolutions obtained here with those that this indicator expresses. Before comparing these evolutions it is important to realise that the DRC indicator characterises the total domestic energy demand while the aggregates only convey the evolution from the electricity and gas demands, and that in some future scenarios there are other sources of energy used mainly for heating (district heating in NSP and PR, and biomass in FWp). Therefore, the evolutions from Table 7.3.0.4 have to be transformed.

For the calculations, it is assumed that these other energy sources are only used for heating purposes. Section 6.5.7 shows that in the base scenario (UK) 10% of the households do not use electricity or gas for heating purposes. Therefore, the data do not contain information on the energy these households use for heating, and so, the evolutions cannot account for these share of households. In consequence, it is assumed that their energy demand for heating follows the general evolution.

Currently, around 80% of domestic energy is used for heating (Palmer & Cooper, 2013). At the same time, only a fraction of the households which use electricity or gas for heating purposes in the base scenario don't use either of them in the future scenario (if we call this fraction f_o^{Sc}, then $f_o^{Sc} = f_{other}^{Sc} - f_{other}^{Base}$: $f_o^{NSP} = 0.53$; $f_o^{PR} = 0.33$; and $f_o^{FWp} = 0.80$, which makes $f_o^{FW} = 0.52$ —see Section 6.5.7—). This means that $0.80 \cdot f_o^{Sc}$ of the household energy demand in the base scenario has to be transformed into heating energy demand in the future scenarios and added to the aggregates.

The amount of energy used for heating greatly depends on the energy efficiency of the dwellings and, also, on the attitudes of their occupants. Section 6.5.4 shows the effects on energy demand of the dwelling efficiency in the future scenarios ($k^{NSP} = 0.65$, $k^{PR} = 0.70$ and $k^{FWp} = 0.95$) and Section 6.5.2 shows the effects of the attitudes of their occupants ($k^{NSP} = 0.50$, $k^{PR} = 0.75$ and $k^{FWp} = 1.20$). In addition, FWp cannot afford as much biomass as they would need; following the corrections found in Section 6.5.6, the factor 0.74 (average of k from all the groups in FWp) is used for this correction.

These values are used to transform the fraction of the energy demand in the base scenario ($0.80 \cdot f_o^{Sc}$) and are added to the aggregated household energy demands. The resulting aggregated and corrected energy demands per household, the evolution they represent, and the evolutions conveyed by the DRC indicator are presented in Table 7.4.2.1. These are only rough estimates; not only the corrections are subjective, the ratios used have the base scenario as origin and the aggregates mix the outcomes of Edata and Gdata, which both present different base ratios. However, this simple calculation gives a good first approximation to the total household energy demand.

Table 7.4.2.1: Comparison of DRC domestic energy demand evolutions with the corrected aggregates evolutions.

(kWh)	Total domestic energy			
	NSP	PR	MF	FW
Unweighted aggregate	16.56	19.67	31.60	29.35
Weighted aggregate	15.91	19.06	32.54	29.16
	Evolutions			
Unweighted aggregate	−44%	−33%	7%	0%
Weighted aggregate	−46%	−35%	10%	−1%
DRC indicator	−62%	−38%	15%	−3%

The resulting household energy demand evolutions found with the aggregates agree notably well with those proposed by DRC, especially those from the weighted aggregates. The only scenario with significant differences is NSP, the scenario which differs the most from the base. One has to also take into account that the electricity and gas demands for FW are upper limits, as a significant percentage of the population in FWp live in informal settlements. In addition, the aggregates are in all the cases closer to the base scenario than the values proposed by DRC, with the weighted aggregates being systematically closer to the DRC values.

This probably reflects the natural tendency of aggregates to "centre" their outcomes and it highlights the suitability of using weights. However, it also implies that the factors defined for NSP may have been too conservative. In particular, the correction found in Section 6.5.4 for 'Energy efficiency of dwellings' —which greatly influences the corrections used to find the total household energy demand— are based on the relation between the low and highly insulated households groups. However, the DRC indicator states that in NSP most dwellings reach passivhaus standards and, since the base U value is 0.24 W/m^{2}K and passivhauses reach 0.10 W/m^{2}K, it would imply a correction of the order of 0.45 instead of 0.65 (and of the order of 0.55 instead of 0.70 for PR). This highlights the importance of carefully following the characteristics of the indicator when obtaining the corrections and/or ratios for each group in each scenario.

7.5 Summary and conclusions

This chapter had two main aims. The first one was to make aggregates with the projections produced in the previous chapter in order to obtain a general picture of the energy demand in the future scenarios. The second one, to explore the reliability of the information these aggregates tell about the household energy demand in the future scenarios. For that, two sets of aggregates have been obtained by means of weighted sums, one without giving any explicit weight to the projections (*i.e.* all projections have the same weight) and one giving each projection a particular weight. This allowed their comparison and an analysis of the extent to which these aggregates diverge. This analysis allows to evaluate the role of the weights in the results of the aggregates and, therefore, to assess the likely reliability of the information they convey.

The weights for the weighted aggregate were derived following three criteria: (1) define a general weight accounting for the importance of each projection, (2) decrease the weights of dependent variables by accounting for their degree of dependency, and (3) increase the weights of the variables which drive each scenario. It is important to stress that only notable dependencies are needed to be taken into account in criterion (2), as the effect in the aggregates of subtle changes in weights are negligible.

Once the aggregates for the energy demand per household were obtained, the total energy demand and the energy demand per person in the scenarios were calculated. Finally, all the information conveyed by the aggregates were analysed and compared. These analyses show that, in order to obtain reliable aggregates of the energy demand per household, the work to obtain projections must be taken seriously as, although isolated misjudgements do not significantly affect the aggregates, the accumulation of inaccuracies —especially if their effects are not randomly distributed— may significantly affect them. In addition, there are some variables which do dramatically affect the results since they act on the whole aggregates, rather than affecting only single projections. The population size and the household size of the scenarios greatly influence the results obtained from the aggregates, and the fraction of population using gas particularly influences the total gas demanded in the scenarios. Therefore, it is imperative to make sure no misjudgements are made when developing these variables if a meaningful picture is to be obtained for total and per person energy demands in the scenarios.

Aggregates do not need to seek a general view of the household energy demand. Each projection conveys a particular bit of information. Therefore, one can also study particular aspects of this domain by aggregating the projections of specific variables. The decision of which projections to aggregate depends on the question that needs to be explored.

A comparison of the evolutions conveyed by the aggregates and the DRC indicator 'Domestic energy demand' shows a notable fit between their values. However, it highlights the tendency of indicators to "centre" their outcomes and suggests that the factors derived for the NSP could be less conservative.

Finally, a brief analysis of the aggregates suggests that an effort to make the energy networks flexible and the electricity one bi-directional seems pertinent. At the same time, it shows that increasing or decreasing these capacities does seem much less appropriate, as such measures would not perform well in all the scenarios. In addition, one has to take into account that in most scenarios the energy demanded by households is not limited to electricity and gas, and that the variables 'Time spent at home' and 'Microgeneration' could not be projected. The aggregates obtained here can be useful for the planning of the future electricity and gas grids. However, if what is sought is to have a glimpse in the whole picture of the household energy demand, it is mandatory to analyse and evaluate other sources of energy used by households in different scenarios.

Part IV

Discussion and conclusions

Chapter 8

Discussion

Plan for the future because that's where you are going to spend the rest of your life.

— Mark Twain

8.1 General discussion

The main outcome of this thesis is the development of a scenarios-based tool capable of projecting disaggregated data into future scenarios and the methods to use it. Other valuable outcomes presented here are: (1) a methodology to supplement with new indicators common scenarios (those with an architecture comprising a general narrative plus the characteristics of a set of indicators), (2) a set of indicators complementing the scenarios of DRC with detailed information related to households and the way they use energy, and (3) the evolutions that the household electricity and gas demand data from the CER smart metering trials follow when projected with the tool into the extended DRC scenarios. These outcomes are presented together in Section 8.4 to make their consultation easier.

The introductory part of this thesis, Part I - *Scene-setting and context*, explains in Chapter 1 why it is important to provide such tool, the goals of the thesis and how it has been structured; and in Chapter 2 it gives some background and a review of the literature related to future urban scenarios and energy demand in households. In Part II - *Methodology development*, a brief explanation of the theoretical framework of future studies and that followed in this thesis is given in Chapter 3; subsequently, the scenarios from DRC are adapted in Chapter 4, and the tool is developed in Chapter 5. In the results part, Part III - *Projecting household energy data into future scenarios*, the factors needed for the projections are derived and the projections obtained in Chapter 6, and the resulting aggregates calculated in Chapter 7.

The literature reviews presented in Chapter 2 provide an understanding of the determinants of household energy demand and of the state of the art of urban future scenarios (Objective (1)). This understanding is used in Chapter 4, where a set of indicators characterising the main determinants of household energy demand missing in DRC are developed (Objective (2)). Their process of development demonstrates how scenarios with a similar architecture to that of DRC —a general narrative plus the characteristics of a set of indicators (Figure 4.1.1.1)— can be complemented and adapted to specific user needs or domains of study. Most of the scenarios developed within the futures community have such an architecture, therefore, they hold the potential to be adapted with the method described there and presented in a generalised way in Section 8.4.1. A case study shows how these additions can seamlessly be used with the original scenarios in a futures analysis. This use is outside of the scope for which the additions were developed —the projection of disaggregated household energy demand data—, therefore demonstrating their flexibility. All that reinforces the extensive evidence from the futures literature in that scenarios are powerful tools to help thinking about the future. In addition, the development of the new indicators train the reader in the process of futures thinking and scenario building.

The mathematical framework presented in Chapter 5 is a simple tool to project disaggregated data into future scenarios (Objective (3)). In Chapter 6, this tool has been used to project disaggregated household energy demand data into the scenarios of DRC complemented with the indicators characterised in Chapter 4, demonstrating the performance of the tool (Objective (4)). Subsequently, in Chapter 7, aggregates for each scenario have been obtained with these projections. The evolutions these aggregates show with respect to the data samples are presented in Table 7.3.0.4 and Section 8.4.4. Finally, this discussion and subsequent sections analyse the usefulness of the tool and in what ways it can improve the decision-making process (Objective (5)).

As expected, the projections consisting only on corrections show the same profile as the base shifted upwards or downwards, and the behaviours of the projections obtained with ratio-weighted sums show an intricate mix of the behaviours of each group. The differences between scenarios are larger for projections consisting of corrections. This is mainly because the differences between the group's energy demands and between their ratios are usually not dramatic.

In some cases the effects of the changes in a variable are difficult or impossible to quantify. This is mainly because the indicator(s) on which the variable is based is vague (this makes the definition of groups and factors unclear), these effects themselves are uncertain (this is the reason why no indicator characterised the use of energy-storage technologies, for example), or the variable itself is difficult to define or measure. Some of the variables which influence gas demand the most are difficult to define and measure; for example, a variable accounting for the temperature at which a dwelling is kept. Such variable would be difficult to define as different rooms may be kept at different temperatures, these temperatures may differ depending on who occupies the room and the outside temperature, etc. In addition, it would be difficult to reliably obtain the information about such variable in a survey.

The definitions of the variables have to accommodate the information in the metadata. For this reason, sometimes the variable defined can fall short (for example when a proxy is used —'Number or rooms' conveys much coarser information than 'Usable floor area'—) or can convey slightly different information (the information introduced by 'Percentage of children in the household' is not the same than that introduced by 'Age distribution').

The process needed to prepare the projections, grouping sub-samples of data based on their distinct "values" with respect to a variable and analyse the behaviour of the groups, has proven useful to provide good insights about the characteristics of the data. For example, it has shown that in the samples analysed, the variable with the most influence in the electricity demand per household is 'Appliances ownership and use', in the gas demand per household is 'Number of bedrooms' and in both, the electricity and gas demands per person is 'Household size'. Something similar happens with the different projections forming an aggregate. Being able to analyse the different contributions to the aggregate (the projections), provides good insights about the influence each variable has on the future of the data.

Two sets of aggregates have been produced in Chapter 7, one set averaging the projections (*i.e.* all have the same weight) and one set with a weighted sum of the projections. The weights defined accounted for the importance each variable has on determining the household energy demand, the dependencies between variables and their importance in each scenario. From the aggregates generated, the weighted ones are clearly more distant from the base than the averages. The reason is that the weights mostly emphasise those projections which follow the driving characteristics of each scenario, which are the ones which mostly contributed to their deviation from the base in the first place. However, the differences between weighted and unweighted aggregates are small. This is, in part, due to the number of projections aggregated —for weights of a similar range, the more projections are aggregated, the more similar the result is to an average—. In general, for a given scenario, the differences between the projections of the electricity demand are larger than those between gas projections. This suggests that the groups of households could probably be better defined for the gas projections.

The fact that the differences between aggregates (unweighted vs weighted) are significantly smaller than these within aggregates (scenario vs scenario), even though the range of weights is wide (4.8x), is satisfying. This indicates that the resulting aggregates are robust and that what is significant to determine their behaviour is the accumulation of methodical differences accentuating the scenarios' characteristics. However, an accumulation of inaccuracies holds the potential to have significant effects on the aggregates. It is for this reason that the work needed, from defining the variables and their groups to obtaining the aggregates, cannot be taken lightly.

In order to obtain the energy demands per person and total, the household size and the total population of the scenarios, as well as the fraction of households using gas for the gas demand, have to be used. As the values of these variables influence the aggregates as a whole instead of only affecting one projection, their impact in the outcomes is disproportionate. Therefore, it is crucial that their derivation is well grounded.

The main conclusions obtained from the analysis of these aggregates are that total household electricity and gas demands tend to decrease. Only in FW these increase —between 36% and 51% depending on the aggregate and energy source—. The decreases are very substantial in the rest of the cases —down to a 97% decrease— except by the electricity demand in PR, where the decrease is of less than 6%. As it was not possible to project the variable 'Microgeneration', and there is an increase in their adoption in all scenarios, the electricity demand in all of them is overestimated. Similarly, it was also impossible to project the variable 'Time spent at home'. Therefore, in order to obtain the full picture of the future household electricity and gas demands, the effects of these variables have to be taken into account. Besides, households use additional sources of energy in most of the scenarios. To obtain a complete picture of the household energy demand in the future, these have to be taken into account as well.

A deep analysis of how the evolutions found here could improve decision-making and planning of the future household energy demand infrastructure is outside the scope of this thesis. However, it is apparent that the total electricity and gas demands in the different scenarios are very divergent. Therefore, preparing the energy networks for being flexible so that their capacity can easily be increased or decreased without losing major investments seems to be an appropriate measure. In addition, one beauty of working with scenarios is that, even when it is not possible to project a variable, as long as the scenario contains information about it, this information can be taken into account in the analysis of the data. For example, a brief analysis of the aggregates plus the information conveyed by the indicator 'Adoption of domestic (or community) microgeneration' implies not only that the electricity demand found for each scenario is overestimated, but also that in most scenarios there will be periods where households will over-generate electricity resulting in a net export to the grid. Therefore, making the electricity network bi-directional and planning uses for the excess of electricity may be beneficial.

Even though it was not possible to obtain a complete picture of the household energy demand in the future, the evolutions obtained and the futures analysis they provoke reduce the uncertainty faced by decision-makers when designing interventions, plans or regulations affecting this demand. It does so by identifying and quantifying a range of plausible paths that this demand could take in the future. One way to reduce the uncertainty even further would be by using the tool with other household energy demand data. This could broaden the results obtained with the analysis here, especially if it were possible to project the variables which were not possible to project in this thesis. In such a case, another option would be to apply the evolutions found for these variables to the data used here. With this, one can simulate the missing projections and add them in the aggregates. In addition, using the tool for other —related— domains would allow a similar analysis which, by reducing the uncertainty in these domains, may help drawing a general picture and improve decision-making even further.

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In general, each projection simulates the effects on the data sample of a particular variable changing its behaviour to follow the characteristics of the future scenarios. For a given scenario, one projection conveys the implications of varying a single variable. Yet, it is common to require the study of the evolution of a whole domain in the future scenarios. For that, a number of projections following the characteristics of a set of variables have to be obtained. However, there is usually a high degree of interconnectivities and complexity between any possible set of variables determining the domain. Therefore, it is typically difficult —or impossible— to find a set of independent variables which cater for all the determinants of the data in such domain without some degree of overlapping and gaps between these variables.

These interconnectivities and complexity are, at the same time, the reason why finding a "correct" and systematic process to combine projections of different variables in a single aggregate is a complex matter outside the scope of this thesis. A manual combination of different projections accounting for the relation between the variables projected and how they affect the behaviour of the data in the scenarios is always feasible when these relations are known.

For example, in Chapter 7, weighted sums where the weights are defined taking into account these factors are used to obtain the aggregates. In addition, unweighted sums have also been obtained and their results are not significantly different. This suggests that the relation between variables and how they affect the data in the scenarios does not have a large effect in the aggregates found here. However, this is not a general proof; different scenarios are usually driven by different variables and in different degrees, in some cases heavily driven by them. In these cases an aggregate made up of the few key projections may well be more representative than one comprised of many projections where all have the same weight and, therefore, the effects of the key projections are highly diluted. Therefore, the projections and aggregates obtained are meaningless without enough understanding of why they are needed, what information they convey, and what is the relation and place of the variables projected in the outcome.

Aggregates can aim to obtain a general view of the domain of study, but they can also aim to study a particular aspect of it. The decision of which variables to aggregate and, to a small extent, the weights given to their projections will depend on the question that one wants to answer —and on which projections are available to aggregate—. Each projection gives a particular bit of information. Therefore, the aim of the aggregates and the information conveyed by each projection must be clear before obtaining any aggregate if they are to be useful. In addition, and as done here, the exploration can go further by transforming the results to different agents —here the energy demand per household has been transformed to energy demand per person and total energy demand in the scenario— to generalise the results and study them at different levels.

Similarly, projections can be used to explore how the behaviour of some data changes when the characteristics of a particular variable vary in different ways. Therefore, the definition of the variable, the groups and their weights may also depend on the question one wants to answer.

The question asked can also influence the method used to aggregate projections. Composite indicators have to be able to quickly and accurately communicate the information needed by decision-makers and users. This is a problem because different ways to aggregate and present them stress different aspects of the reality they convey (Nardo et al., 2005). Although aggregates are not composite indicators, the method chosen to obtain the aggregates presents similar challenges. One advantage of the tool developed here is that it is flexible enough to present the outcomes in different formats (tables, plots), and to portray the whole picture (aggregates) as well as the underlying information (projections, behaviour of the groups). In addition, the process is transparent and, therefore, repeatable and improvable. Studying the different possibilities and arrangements to obtain aggregates and present their outcomes is out of the scope of this thesis and would, without a doubt, be a useful complement to it.

If the data projected are representative of any domain of study, detailed information on the possible future evolutions of the data can be obtained by comparing their behaviour to that of their projections or aggregates. One can, then, assume that the conclusions obtained of their analysis can be broadly applicable to that domain. If the data are not representative of that domain, or other data must be studied, the evolutions found can be applied to other —representative— data in the domain and analysed to investigate their possible futures in the same scenarios. With this, relevant insights about the future of these other data can be gathered. Exactly this is what is suggested here to do in order to inform decision-making related to household energy demand in the UK.

When attempting to apply the evolutions obtained by projecting one set of data to a second one, the two sets of data must not be too dissimilar. This means that they should roughly show the same behaviours and be made up of the same type of agents with not too dissimilar distributions. For household energy demand, for example, if one of the sets of data includes a significant percentage of data from a specific type of dwelling which is not present in the other set, the results may not apply to the other set of data, or will, at least, be less informative than if both sets of data contain the same types of dwellings.

Likewise, if the effects that varying a variable have in the behaviour of the data sets are not similar, the evolutions found with one set will not be representative of the other one.

The process of projecting data, aggregates them. Therefore, when the evolutions found with a set of data are applied to other data, these must be aggregated data or disaggregated data that has been previously aggregated. Here again, to put into context the information that these evolutions conveyed and make sense of their consequences it is necessary to understand what the projections or aggregates express (how the variables and groups had been defined, what variables were included, etc.), what information these evolutions convey and how they fit in their context, as well as their limitations. If these are understood, the information obtained gives details which may be very useful in a futures analysis.

For example, the evolutions obtained here were found using a set of UK scenarios. If a user, unaware of this, applies them to the household energy demand of another country, the outcomes obtained will, in principle, not be reliable. Similarly, UK household energy demand in 2050 will most likely be heavily shaped by electric vehicles. However, this work studies the energy consumed strictly due to the nature of dwellings and the households that use them and, therefore, the variables defined here do not account for the effects of electric vehicles. Analysing the outcomes obtained as if they would account for these effects would lead to incorrect decisions.

The averages used by the tool are not associated with any length of time and can be obtained from any kind of disaggregated data. This gives the projections and their aggregates huge flexibility. For example, one can equally easily obtain the projection of the average daily profile of household electricity demand or that of the average electricity demanded in one year. Not only that, one can also obtain the projection of the household electricity demand for a specific data point (time of day) or the projection of a specific group of households for a specific data point. With the appropriate data, this could be used to explore the effects of particularly sunny hours in a scenario with wide adoption of PV, for example. Additionally, the projection of the total household electricity demand and that of the electricity consumed by a particular appliance are also equally easy to obtain. It all depends on the information the data include; the more detailed the data are, the more detailed the projections and aggregates can be.

As just seen, the outcomes that can be obtained with this tool rely heavily on the information contained in the data projected. Likewise, the method also relies heavily on the information contained in the metadata, which is key in many aspects. It determines whether or not a particular variable can be projected, it must be redefined or a proxy must be found, and it influences the definition and composition of the agents' groups.

When the metadata do not contain information related to a variable, a ratio-weighted sum projection cannot be obtained. The information the metadata contains must be compatible with the variable and with the information in the scenarios, otherwise the variable has to be redefined, a proxy found, or the scenarios adapted. All this directly affects the definition of the agents' groups. At the same time, the composition of the agents' groups for a particular projection directly depends on how the information on the specific variable is presented in the metadata (their granularity, distribution, resolution, whether they are discrete or a progression of values, etc.).

It may be possible that the scenarios into which the data is projected contain indicators on the futures of these or related data. In such cases the outcomes of the projections can be compared to the characteristics of the indicator(s). Most likely this is, effectively, comparing the outcomes of the tool with those of a computer modelling which projected aggregated data. This has been done in Section 7.4.2 where the evolutions found for total energy demand for the aggregates have been compared with the characteristics of the indicator 'Domestic energy demand' from DRC. This comparison shows a notable fit between the values of the DRC indicator and those found for the aggregates. However, it highlights the tendency of indicators to "centre" their outcomes and suggests that the factors derived for the NSP could be less conservative.

Although the tool was developed with the intention to project disaggregated household energy demand data into future scenarios, the temporal standpoint of the scenarios and the type of disaggregated data do not have any intrinsic characteristic needed for the tool to work. This means that the framework can be used to obtain information on how any set of disaggregated data could behave in alternative scenarios where the environment of the data would be different in some aspects. Therefore, a broad spectrum of disaggregated data could be projected into relevant scenarios (*e.g.* star brightness data into alternative universe scenarios, or consumer purchasing behaviour data into different market scenarios). This is especially relevant with the current explosion of data generation: in 2017, 2.5 quintillion bites of data were created every day (DOMO, 2018), a pace which is constantly accelerating. Part of this rapidly growing body of data could be projected into future scenarios in order to obtain information on the evolution of the most varied domains; the possibilities to use the tool and obtain relevant information for the future are huge.

Even so, data can only be projected to existing scenarios and the projections obtained can only convey the evolutions characterised in the scenarios. In addition, the data cannot be projected if the scenarios are too disruptive. As the principle behind the projections is to resize groups of agents in accordance with the future scenarios, when the scenarios include characteristics which are not present in the data, these can normally not be projected. It may be possible, however, to find workarounds to such problems or to obtain partial projections for a portion of the agents' population. For example, a correction may be possible, or it may be that the projections obtained represent a lower or upper limit for the values of the data in the scenario —as is the case with the projections obtained for FW—, or the projections could be adjusted afterwards following the relevant literature.

The tool is very simple in form as well as conceptually. However, its use may be less so. Not only the definition of the variables is usually far from clear-cut, it is often not straightforward to adapt the information in the metadata to that of the scenarios and to find how the variation in the characteristics of the scenarios affect the data. Therefore, relevant literature must often be carefully reviewed, and some degree of expertise in the domain of study and in futures analysis is useful to perform these tasks accurately.

8.2 Tool's contributions to knowledge

Now that the capabilities and limitations of the tool presented here have been discussed, it is pertinent to examine the contributions it provides. These contributions broadly span to three different fields, 1) futures analysis, 2) scenario quantification models and 3) decision support methods used to manage future energy demand, and are subsequently described.

Before tackling these contributions, it is valuable to emphasize that disaggregated data with enough metadata have to be available in order to use the tool, and obtaining them has historically not been a trivial matter. However, the current explosion of data generation suggests that this is changing, making data with enough metadata easier to get hold of. Therefore, the availability of the tool is appropriate in this context.

Tool's contribution to conventional futures analysis

As the tool developed here is an addition to future scenarios to provide them with more detail, to evaluate the contribution the tool brings to conventional futures analysis it is appropriate to compare their requirements and the information provided.

In order to define the variables and groups to use the tool, one needs extensive knowledge about the determinants of the data's behaviour in the specific domain. To derive the factors (corrections, ratios), reasonable knowledge of the future scenarios is also required. This knowledge has to be much deeper if the development of new indicators and, especially, new scenarios are needed. In addition, to manage the data and obtain results, some kind of programming language is almost indispensable.

However, to provide any kind of futures analysis extensive knowledge of the topic and of foresight methods are anyway mandatory. Therefore, assuming suitable data are available, the main additional burdens the use of this tool poses in comparison to other forms of futures analysis may be the ability to manage the data —which is currently easy to outsource— and the availability or not of ready-to-use scenarios. This means that, at the very least for the case of household energy demand in UK —for what detailed scenarios are available here—, the price to pay to use this tool is small. In contrast to this small price, one can obtain specific, direct and quantitative insight about the plausible futures of the household energy demand in this case, or of any other domain of study in the general case.

Tool's contribution to scenario quantification models

The tool presents several advantages in comparison to modelling data projections used to quantify future scenarios. The main ones are the use of disaggregated data and of separate projections for distinct variables, as well as its flexibility, simplicity and transparency.

The use of disaggregated data makes the outcomes of the tool more specific by directly reflecting the effects of varying the data population's composition (different ratios of agent groups). Projecting distinct variables separately reveals the information about the behaviour of each variable in each scenario. This uncovers the different contributions to the final outcome —the projections and the behaviours of the different groups of agents—, which are hidden when applying a general trend to aggregated data.

Although the tool developed here is not straightforward to use, its conceptual and mathematical simplicity contrasts with the complexity of the models typically used to quantify future scenarios. This translates into not requiring high level of skills to operate it, and the tool being extremely flexible and transparent. While conventional models are quite rigid in their application and opaque, this tool can project any set of aggregated data into any scenario with a typical architecture, and makes the assumptions used for its projections (variables, groups, ratios and weights) transparent. Not only that, its reliance on time averages which are not associated to any particular time length, expands its flexibility into the temporal dimension of the data projected (*e.g.* one can project the data for a given day or for one year). And its ability to project any set of disaggregated data expands this flexibility further to the type of agents which produced the data (*e.g.* one can project data of the electricity demanded by a household or by a specific appliance).

Tool's contribution to traditional energy system models

Traditional energy models are of great importance since they are capable of assessing, describing and analysing in great detail the most probable futures of the energy system and draw optimal paths to reach them. With this information, the design of the system can be improved. However, forecasted energy demands often deviate from actual demands (Bhattacharyya & Timilsina, 2009). This is a problem for energy models, which are mostly prediction-based. These models examine a narrow probability space usually defined by a reference projection or business as usual scenario, which is obtained based on past trends and historical data or by a mix of technologies. This can be complemented with a small number of scenarios obtained by introducing variations in some of the assumptions used for the reference scenario (*e.g.* economic growth or demographics). However, this approach makes it impossible for these models to account for discontinuous developments or unexpected shocks (*e.g.* the financial crisis of 2008). When such events occur, they may render the models' outcomes inadequate, as some of the assumptions in which they are based may be too inaccurate (Bhattacharyya & Timilsina, 2009; Koppelaar et al., 2016; Zafeiratou & Spataru, 2014).

On the other hand, the tool's use of explorative scenarios is not based in the predictive paradigm but in exploring what is plausible; exploring a wide plausibility space instead of a narrow probability space. Explorative scenarios change the approach from the search of an optimal or technically favourable system design for a narrow set of forecasts, to the search of a system design that performs well under a range of plausible futures. This approach may result in a less optimal system design when the future unfolds without surprises but it helps the user in searching for solutions that make it resilient to discontinuous progress. Such an approach is particularly important when facing transition periods like the current, where developing countries aim to break away from past demand trends and most developed countries are starting to attempt an energy transition to lower their GHG emissions. What is "exceptionally complex" for standard energy models —accounting for unexpected events— (Zafeiratou & Spataru, 2014, p. 9 (450)), is a natural feature of explorative scenarios.

The explorative scenarios approach integrates socio-political-technical interactions. This enables a "shift from solution analysis" paradigm to a "*solution discovery* and *problem analysis*" paradigm (Koppelaar et al., 2016, p. 12 (1542)) that facilitates finding resilient policies that can cope with technological, political and societal shifts. This ability to explore problems that may arise, not only macro-economic shifts but also political or societal paradigm changes, and the integration of human behaviour is also something that traditional energy models are not capable of (Koppelaar et al., 2016; Pfenninger et al., 2014).

Energy demand is typically nothing but one of the assumptions used in energy models. It can be endogenously calculated from other factors (such as GDP or demographics) or introduced as an exogenous assumption (Zafeiratou & Spataru, 2014). This opens the possibility to use the energy demands found with the tool to feed other models —for example soft-linking them— so that these can explore a wider range of plausible futures and be better equipped to analyse discontinuous developments. Certainly, attention would need to be then put to define the modelling assumptions coherently with the scenarios from which the energy demands were obtained.

Something similar could be done after the outcomes of a model are found. Solutions found based on these outcomes could be tested against explorative scenarios and their energy demand. The scenarios' energy demand found with the tool could supplement DRC to evaluate the resilience of such solutions.

In addition, energy models typically characterise the energy demand by assigning a growth rate per year (Zafeiratou & Spataru, 2014) and use aggregated data and trends to do so. As explained in the previous section, the use the tool makes of disaggregated data uncovers the different contributions to the energy demand obtained and directly reflects the composition of the scenarios' population.

The flexibility, simplicity and transparency of the tool, which in the previous section are identified to be an asset in front of conventional methods to quantify scenarios, are an advantage in front of typical energy models as well. These models are usually opaque and inaccessible and, although some are flexible enough to be used in different environments, the degree of flexibility of the tool presented here is significantly higher. Particularly, it can transfer the analyses and advantages described above for the energy systems to any field of study.

The simplicity and transparency of the tool facilitate the understanding of the assumptions used to obtain its outcomes. Such understanding is fundamental to ensure any solution or policy implication drawn based on them are sound. Only if this understanding exists can the outcomes of a model be used for "insight rather than just numbers" (Pfenninger et al., 2014, p. 10 (83)). In addition, the use of future scenarios characterised by storylines (general narrative and characteristics of a set of indicators) already highlights the general insights that the outcomes of the tool quantify.

As seen in Section 2.2, the landscape of energy models is large and varied, with a great deal of unique blends of approaches and methods used. The landscape of models investigating particularly the energy in the built environment is also wide. However, there is a stark separation between building scale and urban scale in the foci of these methods (Anderson et al., 2015). One of the contributions of the tool is the ability of using information at building scale (energy efficiency of the dwelling, heating type, appliances usage...) in the process to obtaining the energy demand in the scenarios, which can be urban scale or larger.

Additional contributions

In addition to the contributions to knowledge that have been discussed in the previous sections, the use of the tool presents additional value. These contributions that are not directly related either to futures analysis, scenario quantification tools, or energy systems models are described below.

The main additional contribution is the possibility to use the tool as a systematic data analysis framework: 1) find determinants of data behaviour, 2) for each determinant, define groups with distinct behaviours and study them, 3) for each determinant, study aggregated data behaviour when ratios of groups vary, 4) study overall behaviour when determinants change relative weights. The exercise of obtaining aggregates is a rather laborious process that mandates studying the data, thus helping the user to understand better their behaviour. This process also entails understanding the scenarios used and reflecting on how each variable varies in each of them.

To conclude, the availability of this simple tool may spur the development of other tools, methods or models to easily simulate data in different futures, the development of new scenarios (characterising different regions, futures or specific domains), or the adaptation of already developed scenarios to give detailed information of any domain that needs to be studied.

8.3 Improving decision-making

The main means for improving decision-making that the tool presented in this thesis offers is clear: produce aggregates with the relevant projections in the domain that needs to be studied, analyse them and use these analyses to inform decision-making. However, there are some subtilties, not straightforward ways to use the tool and ideas that have been mentioned over the text and can be used to obtain more detailed information on the range of plausible paths that the future can bring or to expand the information obtained. In order to facilitate decision-making, these ideas are briefly reviewed below.

First of all it is convenient to perform a futures analysis of the variables affecting the domain in study before using the tool, although it does not need to be deep as the depth will be provided using the tool. For this, these variables and the scenarios into which they will be projected have to be known. The futures analysis will make the user familiar with these variables and scenarios, and, particularly, with the indicators involved in the study. In addition, it will help to already define a range of distinct plausible paths that the domain could take in the future.

During the process of grouping agents based on their distinct "values" with respect to a variable and analysing the behaviour of these groups, many important insights about the characteristics of the data and of the agents that produce them can be found. This information can be used in the decision-making process or to improve data collection. For example, if the behaviour of the data of a specific group is particularly convenient or inappropriate, measures can be taken to stimulate or discourage it. At the same time, as it is typically difficult to obtain detailed data from a whole population, the sets of disaggregated data that can be projected with the tool usually contain only a representative sub-sample of that population. Their study can make apparent questions for which data could be plausibly collected and valuable to improve the decision-making process.

Similarly, each projection gives a particular bit of information. Therefore, analysing the different projections obtained for an aggregate provides good insights about the influence each variable has on the data and their future. For example, even though the behaviour of one aggregate may show a tendency, it typically contains projections that show the opposite tendency. As seen in Chapter 2, one of the advantages of using futures scenarios is that anticipating a range of futures allows producing roadmaps and aligning decisions to choose the desired one. Analysing the different projections can help identify key variables in, and understand the root reasons for, the distinct behaviours of the aggregates. This, in turn, helps to better design such roadmaps and decisions.

It is important to restate here that the question that needs to be answered is what has to drive the definition of the variables, groups, factors (corrections, ratios), and projections' weights. Therefore, the aim of the aggregates and the information needed must be clear before starting the analysis. In addition, it may be informative to undertake some sensitivity analysis with these values to evaluate how small differences in their definitions affect the projections and aggregates.

As on occasions insufficient metadata might be available, it is not uncommon that some of the variables which determine the behaviour of the data in the domain of study cannot be projected. In such cases it is important to take into account the characteristics conveyed by the indicator(s) related to these variables when analysing the aggregates and their significance for decision-making.

If no disaggregated data with enough metadata which are representative of the domain of study are available, disaggregated data which are not representative (different location, different distribution of the agents' characteristics, etc.) but present similar characteristics can be projected. The evolutions of their projections and aggregates can then be applied to representative data to perform a futures analysis and inform decision-making.

The evolutions found with one set of data can certainly always be applied to other relevant data to analyse their behaviour in the given scenarios. For example, if they are applied to sets of aggregated data or data without metadata in the same field of study, this will broaden the scope of the outcomes obtained.

Another way to reduce future uncertainty even further is by using the tool with several sets of data. This not only broadens the scope of the outcomes, but it may make possible to obtain projections with one set of data for variables which cannot be projected with another set. In such cases, the evolutions found for these variables could be used to simulate the missing projections and complete the aggregates. The conclusions reached by analysing several aggregates would be more robust and so, the decision-making process would face less uncertainty. In addition, using the tool to project data from sub- or super-domains, or domains related to the specific domain of study would allow similar analyses —*e.g* if the domain of study is the household electricity demand, a sub-domain could be the electricity consumed by specific appliances, a super-domain the household energy demand, and a related domain the household gas demand—. Reducing the uncertainty in these domains may help draw a general picture and facilitate decision-making even further.

Once the outcomes are obtained, it may be also helpful to transform them to obtain the behaviour of different agents. With this, these outcomes can be studied at different levels and form a general view of the domain of study. For example, the aggregates found in Chapter 7 for the household electricity and gas demands were transformed to show the demands per person and for the whole population in the different scenarios.

If the data allows it, it may be useful to take advantage of the fact that the averages used by the tool are not associated with any length of time. Some of the variables may have an effect when averaged but may hold the potential to present different effects in short periods of time. In these cases it is also important to study these effects to better inform decision-making. This can be done for specific projections as well as for their effects in the aggregates. For example, the effects of particularly sunny hours in a scenario with wide adoption of PV can be studied by obtaining projections for selected periods of time.

Broadening the futures analysis performed with the tool with all the options described above may be infeasible, very time consuming, or impossible. It may even be impossible to obtain a complete picture of the future of the domain of study (it is unlikely that the metadata conveys all the information needed to determine all variables). However, any outcomes obtained, the futures analysis they provoke, and the knowledge gained in the process reduce the uncertainty faced by decision-makers when designing interventions, plans or regulations, therefore, it is beneficial.

8.4 Review of outcomes

The main outcome of this thesis is a tool that allows policy-makers to more appropriately consider future uncertainty when planning and regulating how to supply energy into households. This tool fills the gap between the future scenarios literature and the current decision support methods available to manage future energy demands, which lack a simple and flexible tool able to project disaggregated data into future scenarios.

The outcomes provided in this thesis are, in order of appearance: (1) the method to supplement common scenarios with new indicators, (2) the tables of characteristics for the indicators which complement the DRC scenarios with information related to households and the way they use energy, (3) the scenarios-based tool capable of projecting disaggregated data into future scenarios with the methods to use it, and (4) the tables with the evolutions that the household electricity and gas demand data from the CER smart metering trials follow when projected with the tool into the extended DRC scenarios.

8.4.1 Method to supplement scenarios

In Chapter 4, the method to supplement scenarios with an architecture comprising a general narrative plus the characteristics of a set of indicators is presented in a narrated and applied form. Here the method is generalised and presented in a systematic form.

First the indicators have to be defined:

(1) **Identify and rank** the system's attributes that need to be characterised (*i.e* the determinants of the domain of study) in order of importance.

(2) **Synthesise, group and simplify** these determinants: get rid of redundancies between determinants (determinant – determinant) and between determinants and scenarios (determinant – scenarios), and discard the determinants without reliable information to characterise them.

(3) **Define and justify** the new indicators based on the remaining set of determinants. It is also useful to formulate the question that the indicator answers.

Then, each indicator has to be characterised:

(4) **Determine** the value of the indicator in the base scenario (usually this is the current value).

(5) **List** the factors on which the indicator depends.

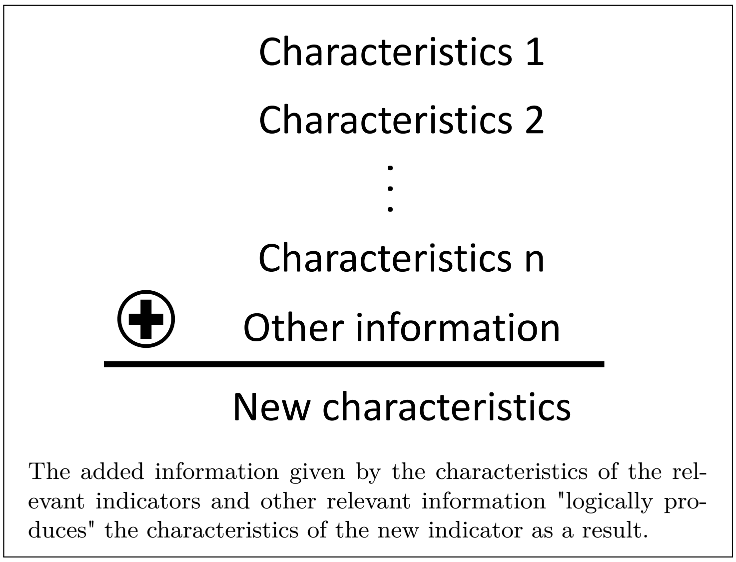
(6) **Find** the characteristics of these factors in each scenario. Use the literature related to the given scenarios if possible, or external literature if needed[1].

(7) **Add** any other related information which is needed or useful to give context (*e.g.* from the general narrative of the scenarios).

(8) **Logically derive** the characteristics of the indicator in each scenario (see Figure 8.4.1.1).

(9) **Iterate** the process as many times as needed to improve internal consistency (indicators are likely to depend on each other).

In addition, it is often useful to write a short review of the information put together for each indicator in each scenario.



The added information given by the characteristics of the relevant indicators and other relevant information "logically produces" the characteristics of the new indicator as a result.

Figure 8.4.1.1: Analogy between the derivation of the characteristics of a new indicator for one scenario and a sum (for reference only; identical to Figure 4.3.0.1).

In the case of discrepancies between the characteristics of the indicators used to derive new indicators and the general narrative of the scenarios, use the information in the general narrative.

Some of the indicators that need to be characterised may depend on many factors which are not characterised in the supplemented scenarios. In some cases this prevents the use of this method and obliges to develop one *ad hoc*. In these cases, it is crucial that the literature used to characterise these factors is as related as possible to the literature used to characterise the original scenarios.

[1] When the detailing of scenarios is inappropriate or lack information and external literature must be used, even if this is from other similar scenarios, additional effort must be placed to ensure internal consistency.

8.4.2 New indicators

Table 8.4.2.1 presents the indicators that complement the DRC with information related to households and the way they use energy, and their characteristics in each of the scenarios. These scenarios are the urban UK versions of NSP, PR, MF and FW. It is recommended to have Section 4.5 at hand when using the results table.

Table 8.4.2.1: Indicators table: characteristics of the new indicators for each scenario (for reference only; identical to Table 4.4.0.1) (continued).

Measure *Base*	UK urban New Sustainability Paradigm (NSP)	UK urban Policy Reform (PR)	UK urban Market Forces (MF)	UK urban Fortress World (FW) (rich|poor)
Adoption of domestic (or community) microgeneration				
% of domestic energy consumption met with microgeneration *1.3% domestic (2016) and 0.1% community (2017)*	⇑ Most domestic energy consumption is met with microgeneration, mainly at the community level.	⇑ A large percentage of domestic energy consumption is met with on-site or community microgeneration.	⇑ On-site microgeneration increases, but the percentage of domestic energy met by it is not very large.	⇑ | ⇓ The overall adoption of microgeneration and the percentage of domestic energy met by it are slightly higher than the current one.
Attitudes to energy efficiency and sustainability				
N/A *Some good intentions, less results*	⇑ People have the will to be sustainable, the information to be so is widely available and rules and society favour it. The result is a very sustainable society with people willing and able to be sustainable.	⇑ People's mindset does not change substantially from the current one. However, the government puts a lot of effort into sustainable measures to make sustainability the default option. Information is reliable and available, making it easier to act sustainably. The result is a society that is more sustainable than currently (but far less than in NSP), in particular the individuals who are engaged.	⇓ Sustainability is far from being a priority for the people, rules do not favour it in any special way, information is still poor and confusing and society does not make it easy to be sustainable. There is no big change in society's sustainable attitudes although they worsen, and society makes it as difficult to be sustainable as currently or more. The result is a society that is less sustainable.	⇓ | ⇓ Rich: governments try to keep up with sustainability measures, but their priority is security. People, locked up in their enclaves, are not —or do not want to be— aware of the rest of the world. Their attitudes to sustainability are almost non-existent. Poor: although some (particularly the youth) develop expectations of fairness and may dream of sustainability, they have many much more urgent issues to deal with.

Table 8.4.2.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
Average dwelling (usable) floor area				
	⇔	⇓	⇓	⇑ | ⇓
Average usable floor area in square metres *Mean total usable floor area of 95 m^2 (2013)*	Although people tend to live together in larger households than currently, the average dwelling's usable floor area decreases slightly. This is mainly due to the increased use of flats rather than houses and is exacerbated by the cohousing movement.	As the household size decreases and there is an increase in typically smaller dwellings (flats), the average dwelling floor area decreases notably.	The average dwelling floor area decreases. The main effect is, however, polarisation: with a strong increase in dwellings with smaller than 50 m^2 of internal floor space and an increase in those with larger than 110 m^2.	Rich: the average dwelling floor area for the rich is much larger than the current one (110 m^2 being close to their lower end). Poor: the average dwelling floor area for the poor is much smaller than the current one. Most of those with dwellings larger than 50 m^2 share them and many cannot even afford to live in formal developments.
Average number and frequency of use of electric appliances				
	⇓	⇑	⇑	⇑ | ⇓
N/A *Almost ubiquitous presence of washing machines, refrigeration and media appliances (2011)*	People tend to have and use appliances less than today.	Appliance use and ownership is similar to the current one, only slightly higher due to smaller households.	Dwellings have a larger number of appliances, and they are more intensively used than today.	Overall there are fewer appliances and these are less used because of the large weight of the poor population (35:65).

Table 8.4.2.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
		Dwelling area per occupant		
	$\Downarrow$	$\Downarrow$	$\Uparrow$	$\Uparrow$ | $\Downarrow$
m^2/person *One occupant every 41.3 m^2 (2011-2013)*	The dwelling area per occupant decreases considerably out of choice (very homogeneously; there is almost no overcrowding).	The area per occupant decreases moderately and homogenously, not by personal choice but due to regulations (*e.g.* favouring flats over houses, which tend to be smaller).	The average area per occupant increases to some extent. However, the main contributors are middle to higher classes; as for a part of the lower classes, it may decrease.	Rich: increase greatly their area per occupant. Poor: decrease greatly their area per occupant.
		Energy poverty		
	$\Downarrow$	$\Downarrow$	$\Leftrightarrow$	$\Downarrow$ | $\Uparrow$
% of population in energy poverty *Around 11.0% (approximately 2.5 million households) (2015)*	Better housing, the almost non-existence of poor people and the government's and society's engagement reduce energy poverty to almost zero.	The decrease in poor people, better housing and the engagement of governments contribute to a strong decrease in energy poverty.	Although inequality increases substantially, the high increase in gross domestic product is able to keep the level of energy poverty similar to the current one.	No energy poverty among the rich. Almost all among the poor are energy-poor.

Table 8.4.2.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
Energy prices (domestic)				
p (penny sterling)/kWh *Electricity (e): 15.47 p/kWh; gas (g): 4.31 p/kWh (2016)*	e⇑ g⇓ The electricity price will increase similarly to that in MF (17.36 p/kWh). The gas price will decrease further than that in PR (3.54− p/kWh).	e⇔ g⇓ The electricity price will be very similar to the current one, 15.25+ p/kWh. The gas price will steadily decrease until 3.54 p/kWh.	e⇑ g⇑ The electricity price will increase almost steadily until 17.36++ p/kWh. The gas price will steadily increase until 6.21 p/kWh.	e⇑ g⇑ The electricity price will increase even further than that in MF (17.36+++ p/kWh). The gas price will increase but less than that in MF (6.21− p/kWh).
Type of building				
% of the building stock *End terrace 10.4%, mid terrace 18.8%, semi-detached 27.6%, detached 22.6%, flat 20.6% (2013)*	Flats: increase. Terraced: similar with the tendency to decrease. (Semi-)detached: decrease.	Flats: increase. Terraced: slight increase. (Semi-)detached: decrease (in particular semi-detached, as people who can afford it prefer to pay more (detached) for increased privacy).	Flats: increase. Terraced: moderate decrease. (Semi-)detached: increase.	Rich: Flats: strong decrease. Terraced: slight increase. (Semi-)detached: strong increase. Poor: Flats: stay the same percentage. Terraced: decrease. (Semi-)detached: strong decrease. Appearance of large informal developments with shacks and tent-like dwellings.

Table 8.4.2.1 – *Continued from previous page*

Measure *Base*	UK urban NSP	UK urban PR	UK urban MF	UK urban FW (rich|poor)
Use of electric space (and water) heating				
% of households using electric space heating *8.5% (2.2 million households) (2015)*	⇑ There is a moderate increase in the use of electric space heating.	⇑ There is an important growth in the use of electric space heating, mainly incentivised by the government. Probably the increase is slightly smaller in electric water heating as technologies such as solar thermal are normally not used for space heating.	⇑ There is a slow increase in the use of electric space and water heating systems.	⇑ | ⇓ The general trend is a slight decrease in the use of electric space and water heating systems. However, it increases within the rich.

A table similar to this one with all the indicators from DRC can be found within the electronic data or downloaded in (DRC, 2012a), and a list of all the indicators in DRC can be found in Appendix A.

N/A stands for not applicable.

8.4.3 Tool

The tool developed here consists of a mathematical framework and the method to use it. With these, disaggregated data can be projected into scenarios as long as three conditions are met: (1) the set of disaggregated data contains sufficient metadata about the agent variables on which its behaviour depends (this only applies to the projections involving groupings), (2) these variables are characterised in the scenarios, and (3) the scenarios are not too disruptive.

Refer to Chapter 5 for detailed information on how to define the groups and the development of the mathematical framework.

Mathematical framework

Let's consider a general set of disaggregated data. These data present the values of 'Φ' produced by agents a, and includes metadata with information about the variables which influence the behaviour of a. The projection of these data into scenario Sc for the variable x_n, *i.e.* the average 'Φ' per agent across the whole agent population in the scenario, is $\Phi_a^{Sc}(x_n^{Sc})$:

$$\Phi_a^{Sc}(x_n^{Sc}) = \Phi_1 \cdot f_1^{Sc} + \ldots + \Phi_i \cdot f_i^{Sc} \tag{8.1}$$

Where Φ_j are the average 'Φ' per agent of each group, f_j^{Sc} the ratios of each group in scenario Sc, and the groups sort agents with the same (or similar) "values" of the variable x_n. If, on top (or instead) of the changes in the group ratios, the projection involves a change in the magnitude of these Φ_j, some corrections must be introduced:

$$\Phi_a^{Sc}(x_n^{Sc}) = k^{Sc} \cdot \left(k_1^{Sc} \cdot \Phi_1 \cdot f_1^{Sc} + \ldots + k_i^{Sc} \cdot \Phi_i \cdot f_i^{Sc}\right) \tag{8.2}$$

Where k^{Sc} is a general correction affecting the whole population of agents and k_j^{Sc} are corrections to the magnitude of each Φ_j. Finally, we can find an expression for the total 'Φ' in the scenario:

$$\Phi_{Ta}^{Sc}(x_n^{Sc}) = F^{Sc} \cdot N \cdot k^{Sc} \cdot \left(k_1^{Sc} \cdot \Phi_1 \cdot f_1^{Sc} + \ldots + k_i^{Sc} \cdot \Phi_i \cdot f_i^{Sc}\right) \tag{8.3}$$

Where F^{Sc} is the ratio in which the total agent population changes in scenario Sc and N the total number of agents.

Expressions for projections with an agent which is not the same as the agent which produced the data can be derived if enough information is available.

Method

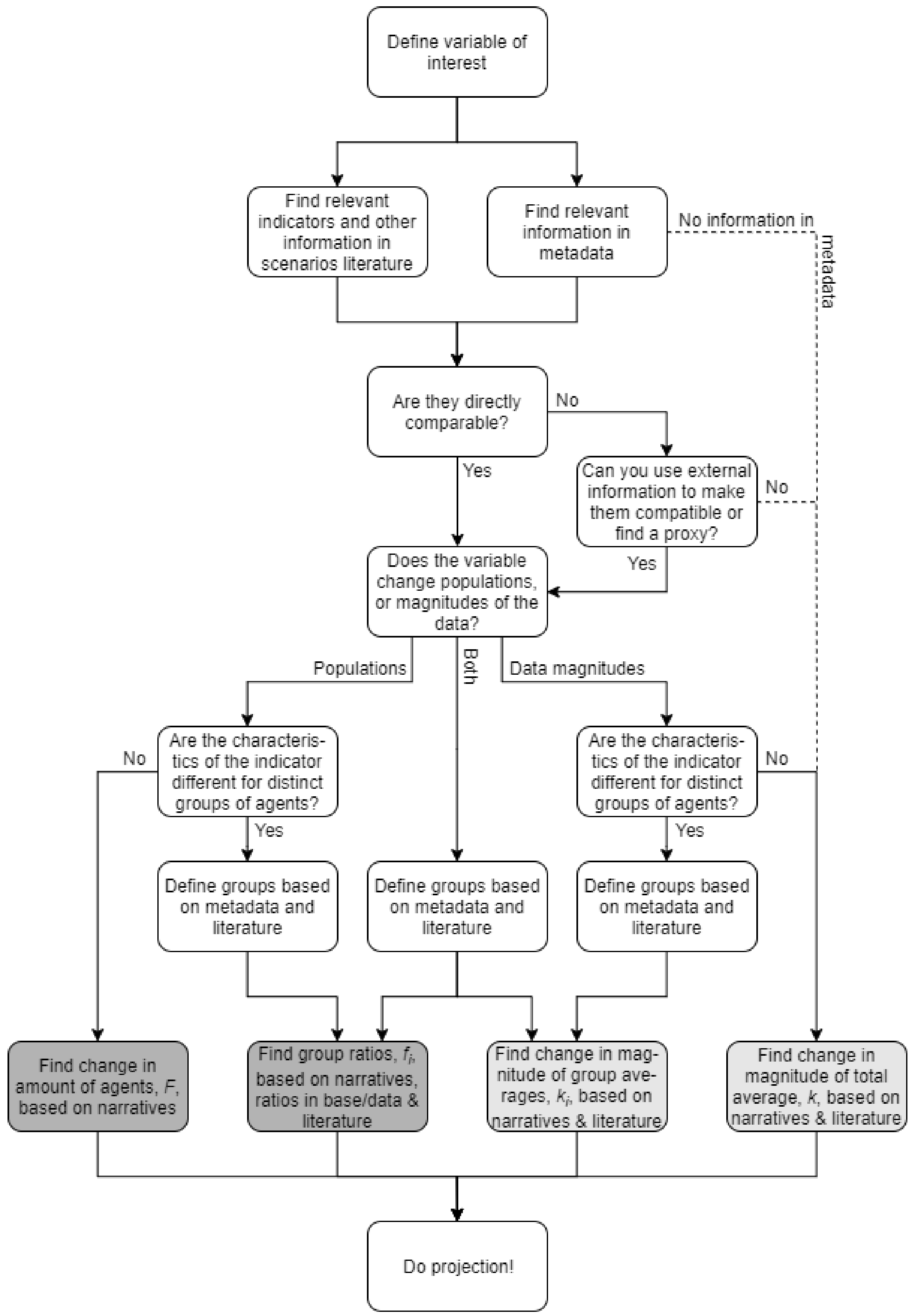
In order to use this mathematical framework, one needs disaggregated data and scenarios fulfilling the conditions previously stated.

The first step is to precisely define the variable or variables of interest. Then one needs to analyse the data and metadata to propose a draft of the groupings. The availability or lack of metadata and their details will influence the choice of groupings or even the definition of the variable(s). Next, one has to find the relevant indicator(s) and other information related to each variable in the scenario literature. If these are not directly compatible with the metadata, one can use external information to transform the metadata and propose the final groupings. If this is not possible, sometimes a proxy can be found in the metadata which can be used instead (*e.g.* use number of bedrooms as proxy for dwelling size). In case of total incompatibility or no information in the metadata, one could still estimate a general correction, k^{Sc}, following the characteristics of the scenarios and any relevant literature. This is then, however, not a real projection but a general correction of the data; *i.e.* if the metadata contained information about the variable, the projection may have needed a ratio-weighted sum. This same procedure is used when the scenario narratives show that the effect the variable has in the scenarios is to change the magnitude of the data values homogeneously. In this case the general correction corresponds to the projection of the data.

When the information from the scenarios and that in the metadata are compatible, and the scenarios indicate that the characteristics of distinct groups of agents are different, the ratio-weighted sum will be used. To do that, one needs to find the ratios of the groups in the base scenario, in the data set, and derive the ratios in the scenarios following their characteristics. The process of finding the group ratios in the scenarios may be more or less straightforward. It depends on whether or not external literature is needed, the ratios in the base scenario and in the data are similar, and on the scenario characteristics. Finally, one can use these ratios, f_j^{Sc}, to do the projection. In some cases, when the characteristics of the scenarios indicate it, a correction has to be found for each group, k_j^{Sc}, to do the projection. Other times, when group ratios do not change but the magnitude of electricity demand does, only these corrections are needed.

Finally, when the variable conveys information of a change in the total population of agents, F^{Sc} has to be found and applied to the relevant equation.

Figure 8.4.3.1 is a flowchart portraying this method. Light grey nodes indicate a correction which affects the magnitude of the data values, and dark grey indicate a change in the total number of agents or in the size of the groups of agents.



Light grey indicates corrections which affect the magnitude of the data values, and dark grey indicates corrections or ratios which affects the total agent population or the size of the agent's group. Dashed line indicates estimation, not actual projection.

Figure 8.4.3.1: Flowchart of the method to apply the mathematical framework (for reference only; identical to Figure 5.5.0.1).

8.4.4 Evolutions of household electricity and gas demands

Table 8.4.4.1 shows a reproduction of the household energy demands evolution for each scenario found with the aggregates obtained in Chapter 7.

Table 8.4.4.1: Resulting evolution relative to the base of the daily household energy demands in each scenario found with each aggregate (for reference only; identical to Table 7.3.0.4).

Unweighted aggregates				
(% of change)	NSP	PR	MF	FW
Electricity per household	−11.89	−9.05	3.43	−7.37
Electricity per person	−39.58	−0.78	37.91	−45.78
Total electricity demand	−46.38	−1.99	36.31	−44.35
Gas per household (gas users)	−11.50	−10.02	3.32	−6.42
Gas per person (gas users)	−39.31	−1.84	37.77	−45.22
Gas per person (whole population)	−96.25	−76.97	46.27	−82.12
Total gas demand	−96.68	−77.26	44.57	−81.65
Total energy per household	−61.07	−50.61	7.16	−44.31
Total energy per person	−73.30	−46.12	42.88	−67.40
Total energy demand	−76.31	−46.78	41.22	−66.54
Weighted aggregates				
Electricity per household	−16.58	−12.65	4.61	−9.13
Electricity per person	−42.80	−4.71	39.48	−46.81
Total electricity demand	−49.24	−5.87	37.85	−45.41
Gas per household (gas users)	−19.58	−14.54	7.62	−6.05
Gas per person (gas users)	−44.85	−6.77	43.49	−45.00
Gas per person (whole population)	−96.60	−78.13	52.35	−82.05
Total gas demand	−96.98	−78.40	50.58	−81.58
Total energy per household	−63.27	−52.70	10.35	−44.95
Total energy per person	−74.81	−48.40	47.13	−67.78
Total energy demand	−77.65	−49.03	45.42	−66.93

The evolutions presented in this table are the percentage of change that the energy demands found with the aggregates show in respect to those found with the data —last column in Table 7.3.0.3—. Note that (a) the weights used for the weighted aggregates are those presented in Criterion (3) of Table 7.3.0.1, (b) the unweighted aggregates give each projection the same weight, (c) the factors and groups of households used in each projection are those presented in Tables 6.5.0.1 and 6.5.0.2 (pages 107 and 109), and (d) it was not possible to project two important variables: 'Time spent at home' and 'Microgeneration'

Chapter 9

Conclusions

Whatever you do will be insignificant, but it is very important that you do it.

— Mahatma Gandhi

9.1 General conclusions

This research aimed to provide a simple and flexible scenarios-based tool that, by projecting disaggregated household energy demand data, allows the study of the impact that future uncertainties have on this demand. This aim is intended to fill a gap between the futures literature —where no simple tool is available to project such data into future scenarios— and the decision support methods and tools used to manage future energy demands —which mostly produce business as usual projections— to allow policy-makers to more appropriately consider future uncertainty when planning and regulating the future of this domain. This is a particularly important endeavour because buildings have long lifespans during which their environment (social, technological, etc.) may change substantially. Therefore, solutions that seem very appropriate today, even if avoiding past mistakes, may not be useful in a matter of years if this uncertainty is not taken into account during their design phase.

The tool developed in Chapter 5 can reduce this uncertainty by identifying and quantifying a range of plausible paths that this demand could take in the future. The scope of the tool's usage is significantly wider than that marked by the aim, as it can project any kind of disaggregated data (it is not constricted to household energy demand) and, therefore, help study the future of any domain.

This tool has been used to project the household electricity and gas demands from the CER smart metering trials into the expanded DRC scenarios, which characterise urban UK in 2050. To obtain a complete picture of the plausible future paths of these demands in the UK, projections of the different variables determining the behaviour of these demands have to be aggregated. The same is true in any domain of study for which the tool is used. To develop a "correct" and systematic process to combine projections in a single aggregate is outside the scope of this thesis. In spite of that, the projections obtained for the household electricity and gas demands have been aggregated with two distinct methods. The resulting aggregates are not substantially different, suggesting that these outcomes are robust. The evolutions the data follow in each scenario for both aggregates are presented in Table 7.3.0.4 and in the Section 8.4.4 so that they can be used to study the future of the household energy demand in the UK.

The development of this tool has followed the path marked by the specific objectives set. The first one was to understand the state of the art of the application of scenario planning techniques, especially in the urban environment, and to review the literature on determinants of household energy demand. This led to select the scenarios from DRC as the scenarios where the disaggregated data would be projected, and to discern the most important determinants of the household energy demand that needed to be characterised in them.

Objective two led to supplementing these scenarios with the indicators needed so that they characterise all of these determinants. For this, a method to supplement futures scenarios was developed, see Section 8.4.1 for a generalised and systematic form of this method. This method can be used to supplement any scenario with an architecture comprising a general narrative plus the characteristics of a set of indicators. Objective two also led to the resulting tables with the characteristics of the new indicators in each scenario, see Table 4.4.0.1 or the Section 8.4.2.

The third objective was to conceive and develop the framework of the tool. This has taken the form of a mathematical framework and the method to use it, and it was developed in Chapter 5. The framework was derived using household energy demand as concrete example to make the reasoning behind it easier to understand. However, it was afterwards generalised and it can be used to project any kind of disaggregated data which contains enough metadata about the variables on which their behaviour depends, into any scenario that characterises these variables and which is not too disruptive. The generalised expressions and the method to use the tool are reviewed Section 8.4.3.

The fourth objective was to demonstrate the performance of the tool by projecting disaggregated household energy demand data into the scenarios extended following the second objective. This was done in Chapter 6, where the data from the CER smart metering trials were projected to the extended DRC scenarios. The factors and groupings used for these projections can be found in Tables 6.5.0.1 and 6.5.0.2 (pages 107 and 109).

And the fifth objective was to analyse how the developed tool can improve decision-making, which has been discussed in Chapter 8. It is shown that using the tool provides specific, direct and quantitative insight about the plausible futures of the domain of study, thus reducing the future uncertainties faced by decision-makers. And it also helps the user gain deep insight about the data projected and future scenarios used. In addition, in order to facilitate decision-making even further, subtle ways to expand the information obtained with the tool are also discussed.

The main conclusions resulting from the analysis of the evolutions obtained are that total household electricity and gas demands mostly tend to decrease; only in FW these increase substantially. All decreases are very substantial except for the electricity demand in PR. It was impossible to obtain projections for some important variables, therefore the picture these outcomes show is not complete. In addition, in most scenarios households use other sources of energy in addition to electricity and gas, therefore these outcomes illustrate only a part of the household energy demand.

A deep analysis of how the evolutions found here could improve decision-making and planning related to the future household energy demand system is outside the scope of this thesis. However, some elementary recommendations were given to future-proof the gas and electricity networks.

The tool presented in this thesis is a valuable contribution to the futures studies because it facilitates decision-making by defining and quantifying a range of distinct plausible paths that the domain of study could take in the future. One can produce aggregates with the relevant projections, analyse them and use these analyses to inform the decision-making process.

To produce these projections and aggregates, a series of variables, groups, factors and weights have to be defined. The process of defining them entails a degree of subjectivity which could affect the outcomes. In general, what is significant to determine the behaviour of the aggregates are the methodical differences accentuating the scenarios' characteristics. However, an accumulation of inaccuracies in these definitions holds the potential to have significant effects on the aggregates. For this reason, the work needed to obtain reliable definitions cannot be taken lightly.

Although the tool is very simple in form and concept, it may be difficult to use. The main challenges are usually to define the variables, to adapt the information in the metadata to that of the scenarios, and to find how the variation in the characteristics of the scenarios affect the data. Besides, the information from both, data and metadata, are crucial to determine what projections can be obtained and their forms, and these projections can only convey the evolutions characterised in existing scenarios. In addition, data cannot be projected into scenarios that are too disruptive. However, it is sometimes possible to find workarounds to bypass some of these limitations.

As a consequence, it may sometimes be impossible to obtain a complete picture of the future of the domain of study when using the tool. However, any outcomes obtained and the futures analysis they provoke, even if not complete, reduce the uncertainty faced by decision-makers when designing interventions, plans or regulations and, therefore, it is beneficial. In addition, not only do the outcomes of the tool help decrease the future uncertainty, the exercise of obtaining them makes the users understand the behaviour of the data projected and trains them in futures thinking.

9.2 Limitations of the tool

Although the limitations of the tool have already been discussed along the thesis, it is convenient to list the main ones together.

Its main limitation is that it is constrained by the data, metadata and scenarios used. Projections cannot be more detailed than the data used and, if there is no data for a specific group of agents, it is impossible to obtain their projection; the metadata available dictate for which variables projections can be obtained and the definition of these variables; and whatever is not characterised in the scenarios is not taken into account in the projections. In addition, the information conveyed by the scenarios has to be compatible with that of the metadata, and some variables may be intrinsically difficult to define —which may prevent obtaining projections (*e.g.* it is difficult to define the temperature a dwelling is kept when different rooms are kept at different temperatures at different points in time).

All these limitations make it not uncommon to find that obtaining projections for a given variable is impossible. Therefore, it is unlikely to be able to produce a complete picture of the future of a domain of study. Then, one may need to take into account the characteristics of the indicator(s) characterising such variable when analysing the outcomes of aggregates or of a group of projections.

In order to use the tool expert knowledge of the domain of study and of the scenarios used is needed to derive all the factors employed in the projections and the weights used to aggregate them. In addition, although the definition of these factors has to follow the dictates of the scenarios and the relevant literature, it always carries a degree of subjectivity.

And finally, as in any futures analysis, the outcomes obtained are not empiric or "correct" (see Chapter 3). The objective of the tool is not to produce a "result" which is "correct"; its objective is to systematically aid in the process of thinking about the future in order to produce better solutions which are resilient.

9.3 Suggestions for further research

This thesis presents two novel research methods (the tool to project disaggregated data into future scenarios and the method to adapt scenarios), new indicators supplementing the scenarios from DRC, and the evolutions that household electricity and gas demand present in these scenarios. Therefore, the range of further research and actions that could be undertaken stemming from these contributions to knowledge are wide and varied.

The simplest and most direct possibility to further in the research done for this thesis would be to apply the evolutions of the household electricity and gas demands found here to these demands in the UK and use the suggestions given in Section 8.3 to obtain more detailed and expanded information on the range of plausible paths that these demands could take. An in depth analysis of the information obtained could inform suggestions to improve the decision-making process and planning of the future household energy system in the UK.

The small differences between the projections of the gas demand suggest that the groups of households could be better defined for the gas projections. Therefore, although the differences in the outcomes are expected to not be significant, further iterations in the definition of these groups as well as that of the other groups, the variables, the factors and the weights used to obtain the projections and aggregates may improve the outcomes. However, the information contained in the metadata of the CER trials limit the scope of these improvements. In consequence projecting other household energy demand data could be more efficient to help determine the reliability of the outcomes by permitting to compare them.

There are several suggestions for further research that stem directly from the tool. Study the different possibilities and arrangements to obtain and present aggregates, and develop a systematic method to obtain them would be a useful addition to it. In addition, the tool could be directly used to study other domains described by the DRC scenarios or other sets of scenarios.

The development of a software which, after introducing a data set (in a given format) and the different variables, factors and weights, would produce their projections and aggregates and would allow for their easy visualisation would facilitate their analysis. For example, by allowing the visualisation of how a daily profile varies in time, or by allowing to "zoom in" a specific aggregate to see the projections forming it —and the same for a given projection to see the behaviour of the groups forming it.

Furthermore, the method to supplement scenarios provided here could be used to adapt any (fitting) scenario to be able to do any kind of futures analysis in other domains or locations, including using the tool presented here or the *Urban Futures Method* from DRC.

9.4 Concluding remarks

In conclusion, this thesis provides several and varied contributions to knowledge in the field of futures studies. The most relevant of which is the scenarios-based tool to project disaggregated data. The outcomes of this tool help reduce the future uncertainty by identifying and quantifying a range of plausible paths that the domain of study could take in the future. As a result, decision-making and planning are facilitated.

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Part V

Appendices

Appendix A

List of all DRC indicators

Demography	Economy	Society
• Population • Age distribution • Life expectancy • Average household size • Urbanisation • Urban population density	• Income • Income inequality • Economic migration (into UK) • Work time • Sustainability in business • Technological innovation	• Community cohesion • Civic activism • Attitudes to consumerism • Geographic mobility
Governance	**Planning and land use**	**Energy**
• Governance models • Public service spending • Public land ownership • Public participation	• Land use • Land recycling (infill, brownfield) • Planning policy • Planning adherence	• Total energy demands • Domestic energy demands • Energy efficient user technologies • Energy efficiency of building and urban morphology • Carbon dioxide emissions
Biodiversity	**Urban form**	**Water**
• Urban tree/hedge cover arrangement at city and land class scales • Tree species • Access to public green space • Total amount of green space • Degree of maintenance for ecological features • Quality of strategic planning for biodiversity conservation • Degree of policy protection for ecological features	• Adaptability of buildings and supporting infrastructure to new use • Settlement pattern (city scale) • Settlement pattern (neighbourhood scale) • Cultural and historical associations • Connectivity • Provision of public realm/open spaces • Quality of public realm/open space • Management of public realm/open spaces • Accessibility of public realm/open spaces • Use of underground space • Asset condition • Composition of 'mixed use' • Artificial external lighting quality • Area of city that is artificially lit	• Urban waterbodies structural diversity • Urban waterbodies: amount • Urban waterway ecological quality • Water distribution system pattern at the city scale • Water supply infrastructure: ownership and management • Water sources • Total water demand • Domestic water withdrawal • Daily domestic water consumption • Water efficiency and recycling measures • Quality of water supplies • Mains sewerage • Urban water pollution levels • Impervious/pervious surfaces
Air quality	**Transportation**	**Housing**
• Health effects of air quality • Particulate matter (PM) • Nitrogen dioxide (NO_2) • Ozone	• Transportation fuel type • Passenger road travel (private) • Passenger road travel (public) • Passenger rail travel • Road freight • Road and parking characteristics	• Urban dwelling density • Household overcrowding • Need for affordable housing • Supply of affordable housing • Housing affordability

Appendix B

Figures used to derive 'Energy price (domestic)'

These are the figures used to derive the values for the indicator 'Energy price (domestic)'. Figure B.0.0.1 is a reproduction of an excerpt of the table generation tool from Tellus Institute (Tellus Institute, n.d.-a) showing the values for Western Europe. It shows the amount of energy used in each scenario and the share that each energy source represents.

Figure B.0.0.2 shows at the left side a composite based on figure 3-44 from (Electris et al., 2009), showing the electricity generation shares for Western Europe in 2050 in MF and PR compared to those in 2005 (current values when the document was first released). At the right side it shows a reproduction of figure 6.4.6 from (Greenpeace, 2015), showing the development of the electricity generation costs in the Ref, E[R] and AE[R] scenarios for OECD Europe.

And Figure B.0.0.3 shows a reproduction of table 5.4 from (Greenpeace, 2015), showing the projections for fossil fuel and biomass prices for different parts of the world until 2050. It shows the current (2012/2013) prices for the different fuels, the evolution of these prices starting on year 2000, and their projected prices in the Ref, E[R] and AE[R] scenarios until 2050 for USA, Europe and Japan.

Indicators for Western Europe

		Market Forces			Policy Reform			Fortress World			Great Transition		
	2005	2025	2050	2100	2025	2050	2100	2025	2050	2100	2025	2050	2100
Energy - Primary Supply													
Primary energy (10^{18} J)	74	85	83	74	55	36	30	85	75	51	49	23	10
Petroleum share (%)	42	40	42	41	32	18	4	39	36	28	30	13	6
Natural gas share (%)	23	25	25	24	26	11	1	24	22	21	25	8	1
Coal share (%)	13	12	14	11	4	1	0	13	17	21	3	1	0
Nuclear share (%)	15	13	7	9	10	0	0	14	9	11	10	0	0
Biomass share (%)	5	5	5	7	9	13	19	5	7	8	10	18	23
Hydropower share (%)	2	2	3	3	3	4	6	3	3	4	3	3	5
Other renewables share (%)	0	2	4	5	17	53	70	2	5	6	19	56	65
Energy intensity (MJ/$PPP)	6	4	3	1	3	2	1	4	3	4	3	1	1

Figure B.0.0.1: Excerpt of the table generator tool (Tellus Institute, n.d.-a) showing the energy-related indicators for Western Europe.

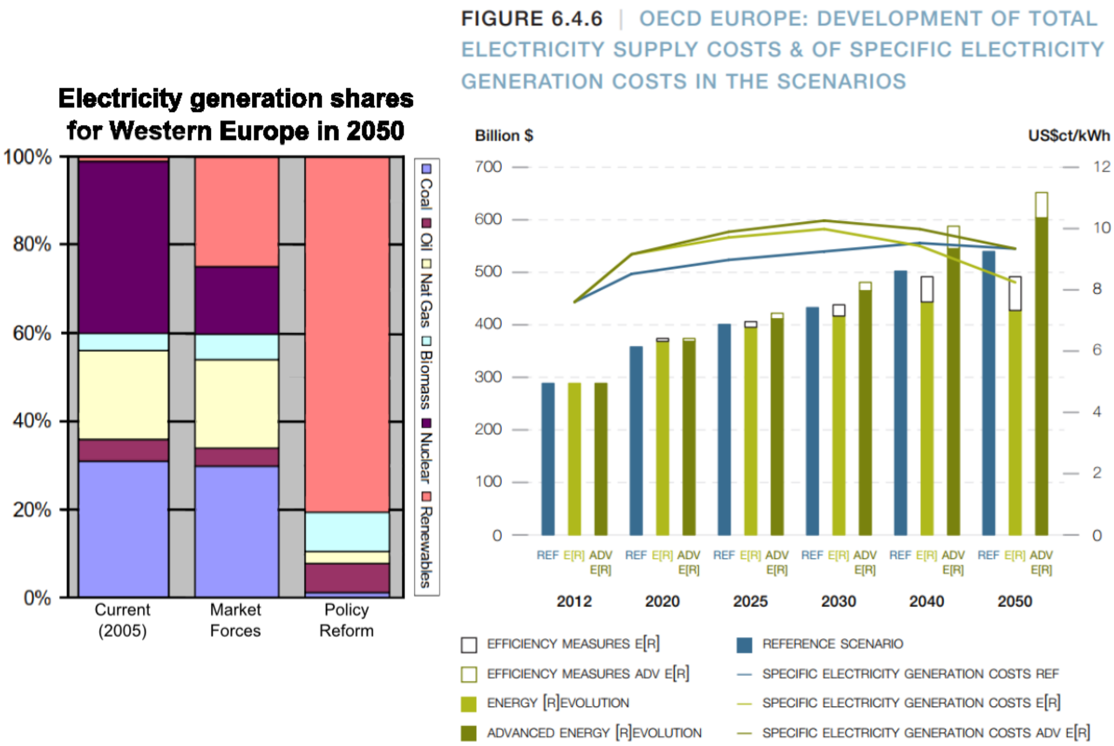

Figure B.0.0.2: Left side: composite based on (Electris et al., 2009) figure 3-44 showing the electricity generation shares for Western Europe in 2050. Right side: reproduction of figure 6.4.6 from (Greenpeace, 2015) showing the development of the electricity generation costs for OECD Europe.

TABLE 5.4 | DEVELOPMENT PROJECTIONS FOR FOSSIL FUEL AND BIOMASS PRICES IN $2010

	UNIT	2000	2005	2007	2008	2010	2012/ 2013	2020	2025	2030	2035	2040	2050
CRUDE OIL IMPORTS HISTORIC PRICES (FROM WEO)	$2013/BARREL	37,1	54,1	81,2	105,2	83,6	106,0						
REFERENCE SCENARIO ACCORDING TO WEO 2014, CURRENT POLICIES SCENARIO	$2013/BARREL						106,0	116,0	127,5	139,0	147,0	155,0	155,0
ENERGY [R]EVOLUTION SCENARIOS ACCORDING TO WEO 2014, 450 PPM SCENARIO	$2013/BARREL						106,0	105,0	103,5	102,0	101,0	100,0	98,0
NATURAL GAS IMPORTS HISTORIC PRICES (FROM WEO)													
UNITED STATES	$2013/GJ	5,4	2,5	3,5	9,4	5,0	3,9						
EUROPE	$2013/GJ	4,0	4,9	6,8	11,8	8,5	11,2						
JAPAN LNG	$2013/GJ	6,6	4,9	6,9	14,4	12,4	17,1						
REFERENCE SCENARIO ACCORDING TO WEO 2014, CURRENT POLICIES SCENARIO													
UNITED STATES							3,9	5,8	6,5	7,2	8,1	9,0	10,8
EUROPE	$2013/GJ						11,2	12,1	13,0	13,9	14,3	14,8	15,6
JAPAN LNG	$2013/GJ						17,1	15,8	16,5	17,2	17,7	18,3	19,3
ENERGY [R]EVOLUTION SCENARIOS ACCORDING TO WEO 2014, 450 PPM SCENARIO	$2013/GJ												
UNITED STATES	$2013/GJ						3,9	5,4	5,8	6,2	6,3	6,4	6,6
EUROPE	$2013/GJ						11,2	11,1	10,8	10,6	10,1	9,7	8,9
JAPAN LNG	$2013/GJ						17,1	14,3	13,8	13,3	13,0	12,7	12,0
OECD STEAM COAL IMPORTS HISTORIC PRICES (FROM WEO)	$2013/GJ	1,9	2,3	3,3	5,7	4,6	3,7						
REFERENCE SCENARIO ACCORDING TO WEO 2014, CURRENT POLICIES SCENARIO	$2013/GJ						3,7	4,6	4,9	5,1	5,2	5,4	5,7
ENERGY [R]EVOLUTION SCENARIOS ACCORDING TO WEO 2014, 450 PPM SCENARIO	$2013/GJ						3,7	3,8	3,6	3,4	3,4	3,3	3,3
SOLID BIOMASS REFERENCE AND ENERGY [R]EVOLUTION SCENARIOS	$2013/GJ						4,2	4,6	4,9	5,2	5,4	5,7	6,3
NUCLEAR FUEL REFERENCE AND ENERGY [R]EVOLUTION SCENARIOS	$2013/GJ						1,0	1,3	1,4	1,6	1,7	1,9	2,3

source IEA WEO 2014 and own assumptions.

Figure B.0.0.3: Reproduction of table 5.4 from (Greenpeace, 2015) showing the price projections for different fuels in different parts of the world until 2050.

Appendix C

Projections: more results and other additions

C.1 More projections results

C.1.1 Attitudes to energy efficiency and sustainability

The following tables are the projections of the daily average energy demand for the variable 'Attitudes to energy efficiency and sustainability' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.2.3.

Table C.1.1.1: Base and projections for winter daily average electricity and gas demand per household and per person.

Winter							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	14.30	7.15	10.72	20.02	17.53	23.09	16.70
	5.29	2.65	3.97	7.41	6.49	7.22	6.38
WD	14.08	7.04	10.56	19.71	17.26	22.65	16.46
	5.21	2.61	3.91	7.30	6.39	7.08	6.28
WE	14.84	7.42	11.13	20.78	18.20	24.17	17.31
	5.50	2.75	4.12	7.69	6.73	7.56	6.61
kWh	Totals Gdata						
AD	43.39	21.69	32.54	60.74	55.26	64.04	51.13
	15.13	7.57	11.35	21.19	19.19	20.79	18.31
WD	43.01	21.51	32.26	60.22	54.75	63.26	50.74
	15.00	7.50	11.25	21.00	19.01	20.53	18.17
WE	44.31	22.16	33.24	62.04	56.50	65.96	52.10
	15.45	7.73	11.59	21.64	19.61	21.41	18.66

Table C.1.1.2: Base and projections for spring daily average electricity and gas demand per household and per person.

Spring							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	11.31	5.65	8.48	15.83	13.87	18.28	13.21
	4.19	2.09	3.14	5.86	5.13	5.72	5.04
WD	11.12	5.56	8.34	15.57	13.63	17.91	12.99
	4.12	2.06	3.09	5.76	5.05	5.60	4.96
WE	11.79	5.89	8.84	16.50	14.46	19.24	13.74
	4.37	2.18	3.27	6.11	5.35	6.02	5.25
kWh	Totals Gdata						
AD	20.50	10.25	15.37	28.70	26.08	29.87	24.26
	7.15	3.57	5.36	10.01	9.06	9.70	8.69
WD	21.13	10.57	15.85	29.59	26.88	30.83	25.00
	7.37	3.69	5.53	10.32	9.34	10.01	8.95
WE	18.89	9.44	14.17	26.44	24.03	27.45	22.39
	6.59	3.29	4.94	9.22	8.35	8.91	8.02

Table C.1.1.3: Base and projections for summer daily average electricity and gas demand per household and per person.

Summer							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	10.32	5.16	7.74	14.45	12.66	16.41	12.10
	3.82	1.91	2.87	5.35	4.69	5.13	4.62
WD	10.21	5.10	7.65	14.29	12.52	16.24	11.96
	3.78	1.89	2.83	5.29	4.63	5.08	4.57
WE	10.63	5.31	7.97	14.88	13.04	16.86	12.46
	3.94	1.97	2.95	5.51	4.83	5.27	4.76
kWh	Totals Gdata						
AD	3.58	1.79	2.68	5.01	4.55	5.10	4.28
	1.25	0.62	0.94	1.75	1.58	1.66	1.53
WD	3.62	1.81	2.71	5.06	4.60	5.14	4.33
	1.26	0.63	0.95	1.77	1.60	1.67	1.55
WE	3.49	1.74	2.61	4.88	4.44	5.00	4.16
	1.22	0.61	0.91	1.70	1.54	1.62	1.49

Table C.1.1.4: Base and projections for autumn daily average electricity and gas demand per household and per person.

Autumn							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	11.86	5.93	8.90	16.61	14.54	19.45	13.81
	4.39	2.20	3.29	6.15	5.38	6.08	5.27
WD	11.58	5.79	8.68	16.21	14.19	18.88	13.49
	4.29	2.14	3.21	6.00	5.25	5.91	5.15
WE	12.58	6.29	9.43	17.61	15.42	20.86	14.61
	4.66	2.33	3.49	6.52	5.70	6.53	5.58
kWh	Totals Gdata						
AD	19.52	9.76	14.64	27.33	24.81	28.12	23.20
	6.81	3.40	5.11	9.53	8.62	9.13	8.31
WD	19.20	9.60	14.40	26.89	24.40	27.65	22.82
	6.70	3.35	5.02	9.38	8.48	8.98	8.17
WE	20.27	10.14	15.21	28.38	25.77	29.20	24.10
	7.07	3.54	5.30	9.90	8.95	9.48	8.63

Table C.1.1.5: Base and projections for the hottest day average electricity and gas demand per household and per person.

Hottest day							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
WD	9.97	4.99	7.48	13.96	12.22	15.97	11.66
	3.69	1.85	2.77	5.17	4.53	4.99	4.45
WE	10.22	5.11	7.66	14.31	12.54	16.69	11.92
	3.78	1.89	2.84	5.30	4.64	5.22	4.55
kWh	Totals Gdata						
WD	2.85	1.42	2.14	3.99	3.63	4.22	3.35
	0.99	0.50	0.74	1.39	1.26	1.37	1.20
WE	3.24	1.62	2.43	4.54	4.14	4.88	3.80
	1.13	0.57	0.85	1.58	1.44	1.58	1.36

Table C.1.1.6: Base and projections for the coldest day average electricity and gas demand per household and per person.

Coldest day							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
WD	15.28	7.64	11.46	21.39	18.74	24.38	17.89
	5.66	2.83	4.24	7.92	6.94	7.63	6.83
WE	16.79	8.39	12.59	23.50	20.60	26.87	19.67
	6.22	3.11	4.66	8.70	7.63	8.40	7.51
kWh	Totals Gdata						
WD	61.52	30.76	46.14	86.13	78.47	91.85	72.27
	21.46	10.73	16.09	30.04	27.24	29.81	25.88
WE	64.42	32.21	48.32	90.19	82.30	97.54	75.33
	22.47	11.23	16.85	31.46	28.56	31.66	26.97

Table C.1.1.7: Base and projections for the comparing seasons daily average electricity and gas demand per household and per person.

Comparing season (Autumn (Edata) and Winter (Gdata))							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	12.16	6.08	9.12	17.03	14.92	19.97	14.16
	4.50	2.25	3.38	6.31	5.52	6.25	5.41
WD	11.89	5.94	8.91	16.64	14.58	19.44	13.85
	4.40	2.20	3.30	6.16	5.39	6.08	5.29
WE	12.86	6.43	9.65	18.00	15.77	21.30	14.95
	4.76	2.38	3.57	6.67	5.83	6.66	5.71
kWh	Totals Gdata						
AD	40.13	20.06	30.09	56.18	51.07	58.48	47.52
	13.99	7.00	10.50	19.59	17.74	18.98	17.02
WD	39.89	19.95	29.92	55.85	50.75	58.05	47.26
	13.91	6.96	10.43	19.48	17.63	18.84	16.92
WE	40.71	20.35	30.53	56.99	51.84	59.55	48.17
	14.20	7.10	10.65	19.88	18.00	19.33	17.25

C.1.2 Energy efficiency of appliances

The following tables are the projections of the daily average electricity demand for the variable 'Energy efficiency of appliances' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.3.3.

Table C.1.2.1: Base and projections for winter daily average electricity demand per household and per person.

Winter							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	14.30	8.86	8.86	15.01	14.64	14.84	14.61
	5.29	3.28	3.28	5.56	5.46	4.64	5.58
WD	14.08	8.73	8.73	14.78	14.42	14.56	14.40
	5.21	3.23	3.23	5.47	5.38	4.55	5.50
WE	14.84	9.20	9.20	15.58	15.20	15.54	15.15
	5.50	3.41	3.41	5.77	5.66	4.86	5.78

Table C.1.2.2: Base and projections for spring daily average electricity demand per household and per person.

Spring							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	11.31	7.01	7.01	11.87	11.58	11.75	11.55
	4.19	2.60	2.60	4.40	4.32	3.68	4.41
WD	11.12	6.89	6.89	11.67	11.39	11.51	11.37
	4.12	2.55	2.55	4.32	4.25	3.60	4.34
WE	11.79	7.31	7.31	12.38	12.07	12.37	12.02
	4.37	2.71	2.71	4.58	4.50	3.87	4.59

Table C.1.2.3: Base and projections for summer daily average electricity demand per household and per person.

Summer							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	10.32	6.40	6.40	10.84	10.59	10.55	10.59
	3.82	2.37	2.37	4.01	3.95	3.30	4.04
WD	10.21	6.33	6.33	10.72	10.46	10.44	10.47
	3.78	2.34	2.34	3.97	3.90	3.26	4.00
WE	10.63	6.59	6.59	11.16	10.90	10.84	10.91
	3.94	2.44	2.44	4.13	4.06	3.39	4.17

Table C.1.2.4: Base and projections for autumn daily average electricity demand per household and per person.

Autumn							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	11.86	7.35	7.35	12.46	12.14	12.50	12.08
	4.39	2.72	2.72	4.61	4.52	3.91	4.61
WD	11.58	7.18	7.18	12.15	11.85	12.14	11.80
	4.29	2.66	2.66	4.50	4.42	3.80	4.51
WE	12.58	7.80	7.80	13.21	12.87	13.41	12.79
	4.66	2.89	2.89	4.89	4.79	4.19	4.88

Table C.1.2.5: Base and projections for the hottest day average electricity demand per household and per person.

Hottest day							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
WD	9.97	6.18	6.18	10.47	10.21	10.27	10.21
	3.69	2.29	2.29	3.88	3.81	3.21	3.90
WE	10.22	6.34	6.34	10.73	10.47	10.73	10.43
	3.78	2.35	2.35	3.97	3.90	3.35	3.98

Table C.1.2.6: Base and projections for the coldest day average electricity demand per household and per person.

Coldest day							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
WD	15.28	9.47	9.47	16.04	15.66	15.68	15.66
	5.66	3.51	3.51	5.94	5.84	4.90	5.98
WE	16.79	10.41	10.41	17.63	17.22	17.27	17.21
	6.22	3.85	3.85	6.53	6.42	5.40	6.57

Table C.1.2.7: Base and projections for the comparing season daily average electricity demand per household and per person.

Comparing season (Autumn 2009)							
kWh	Totals Edata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	12.16	7.54	7.54	12.77	12.45	12.84	12.39
	4.50	2.79	2.79	4.73	4.64	4.02	4.73
WD	11.89	7.37	7.37	12.48	12.17	12.50	12.12
	4.40	2.73	2.73	4.62	4.53	3.91	4.63
WE	12.86	7.97	7.97	13.50	13.16	13.69	13.08
	4.76	2.95	2.95	5.00	4.90	4.28	4.99

C.1.3 Energy efficiency of dwellings

The following tables are the projections of the daily average gas demand for the variable 'Energy efficiency of dwellings' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.4.4.

Table C.1.3.1: Base and projections for winter daily average gas demand per household and per person.

Winter							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	43.39	28.20	30.37	41.22	41.08	41.17	40.48
	15.13	9.84	10.59	14.38	14.32	13.36	14.50
WD	43.01	27.96	30.11	40.86	40.71	40.67	40.17
	15.00	9.75	10.50	14.25	14.20	13.20	14.38
WE	44.31	28.80	31.02	42.10	41.98	42.40	41.25
	15.45	10.05	10.82	14.68	14.64	13.76	14.77

Table C.1.3.2: Base and projections for spring daily average gas demand per household and per person.

Spring							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	20.50	13.32	14.35	19.47	19.40	19.20	19.21
	7.15	4.65	5.00	6.79	6.77	6.23	6.88
WD	21.13	13.74	14.79	20.08	20.00	19.82	19.79
	7.37	4.79	5.16	7.00	6.98	6.43	7.09
WE	18.89	12.28	13.22	17.94	17.88	17.64	17.73
	6.59	4.28	4.61	6.26	6.24	5.73	6.35

Table C.1.3.3: Base and projections for summer daily average gas demand per household and per person.

Summer							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	3.58	2.33	2.51	3.40	3.39	3.28	3.39
	1.25	0.81	0.87	1.19	1.18	1.06	1.21
WD	3.62	2.35	2.53	3.44	3.43	3.30	3.43
	1.26	0.82	0.88	1.20	1.20	1.07	1.23
WE	3.49	2.27	2.44	3.31	3.30	3.22	3.29
	1.22	0.79	0.85	1.16	1.15	1.04	1.18

Table C.1.3.4: Base and projections for autumn daily average gas demand per household and per person.

Autumn							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	19.52	12.69	13.67	18.55	18.47	18.07	18.37
	6.81	4.43	4.77	6.47	6.44	5.87	6.58
WD	19.20	12.48	13.44	18.24	18.16	17.78	18.06
	6.70	4.35	4.69	6.36	6.34	5.77	6.47
WE	20.27	13.18	14.19	19.26	19.18	18.77	19.08
	7.07	4.60	4.95	6.72	6.69	6.09	6.83

Table C.1.3.5: Base and projections for the hottest day average gas demand per household and per person.

Hottest day							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
WD	2.85	1.85	1.99	2.70	2.70	2.71	2.65
	0.99	0.65	0.70	0.94	0.94	0.88	0.95
WE	3.24	2.11	2.27	3.08	3.07	3.14	3.01
	1.13	0.73	0.79	1.07	1.07	1.02	1.08

Table C.1.3.6: Base and projections for the coldest day average gas demand per household and per person.

Coldest day							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
WD	61.52	39.99	43.06	58.44	58.30	59.05	57.21
	21.46	13.95	15.02	20.38	20.32	19.17	20.49
WE	64.42	41.88	45.10	61.20	61.09	62.70	59.63
	22.47	14.60	15.73	21.35	21.29	20.35	21.35

Table C.1.3.7: Base and projections for the comparing season daily average gas demand per household and per person.

Comparing season (Winter 2010-11)							
kWh	Totals Gdata						
	base	NSP	PR	MF	FW		
					All	FWr	FWp
AD	40.13	26.08	28.09	38.12	37.99	37.59	37.62
	13.99	9.10	9.80	13.29	13.25	12.20	13.47
WD	39.89	25.93	27.92	37.90	37.76	37.32	37.41
	13.91	9.04	9.74	13.22	13.17	12.11	13.40
WE	40.71	26.46	28.49	38.67	38.56	38.28	38.14
	14.20	9.23	9.94	13.49	13.45	12.42	13.66

C.1.4 Percentage of children at home

The following tables are the projections of the daily average gas demand for the variable 'Percentage of children at home' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.5.4.

Table C.1.4.1: Base, projections and groups for winter daily average electricity and gas demand per household and per person.

Winter											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	14.30	13.84	13.83	14.06	15.73	16.30	15.64	12.97	17.60	16.88	19.79
	5.29	5.52	5.45	5.40	4.72	5.22	4.64	6.03	4.40	4.36	4.02
WD	14.08	13.63	13.61	13.85	15.48	15.99	15.41	12.77	17.33	16.58	19.52
	5.21	5.44	5.37	5.32	4.64	5.12	4.57	5.93	4.33	4.29	3.96
WE	14.84	14.36	14.35	14.60	16.34	17.07	16.23	13.45	18.28	17.61	20.47
	5.50	5.73	5.66	5.61	4.90	5.47	4.82	6.25	4.57	4.55	4.15
kWh	Totals Gdata							Groups base Gdata			
AD	43.39	43.38	43.29	43.31	44.19	45.67	43.02	42.84	45.71	43.03	43.94
	15.13	16.26	16.01	15.77	13.45	15.46	12.50	19.18	11.99	11.39	8.97
WD	43.01	42.99	42.90	42.92	43.83	45.08	42.75	42.39	45.46	42.82	43.68
	15.00	16.11	15.87	15.63	13.34	15.26	12.42	18.98	11.92	11.34	8.92
WE	44.31	44.35	44.26	44.26	45.08	47.14	43.67	43.95	46.32	43.55	44.59
	15.45	16.63	16.37	16.12	13.73	15.95	12.69	19.68	12.15	11.53	9.10

Table C.1.4.2: Base, projections and groups for spring daily average electricity and gas demand per household and per person.

Spring											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	11.31	10.92	10.92	11.11	12.53	12.90	12.47	10.19	14.00	13.57	15.91
	4.19	4.35	4.30	4.27	3.76	4.14	3.70	4.74	3.50	3.51	3.23
WD	11.12	10.74	10.74	10.93	12.28	12.64	12.23	10.05	13.70	13.27	15.55
	4.12	4.29	4.23	4.20	3.68	4.05	3.63	4.67	3.43	3.43	3.16
WE	11.79	11.36	11.36	11.57	13.15	13.57	13.08	10.55	14.76	14.32	16.83
	4.37	4.53	4.48	4.44	3.94	4.35	3.88	4.90	3.69	3.70	3.42
kWh	Totals Gdata							Groups base Gdata			
AD	20.50	20.54	20.48	20.48	20.86	21.32	20.40	20.26	21.79	20.34	20.10
	7.15	7.70	7.57	7.46	6.35	7.22	5.93	9.07	5.71	5.38	4.10
WD	21.13	21.17	21.11	21.11	21.51	21.99	21.03	20.88	22.48	21.00	20.74
	7.37	7.94	7.81	7.69	6.55	7.44	6.11	9.35	5.90	5.56	4.23
WE	18.89	18.93	18.88	18.87	19.22	19.61	18.81	18.70	20.02	18.67	18.47
	6.59	7.10	6.98	6.87	5.85	6.64	5.46	8.38	5.25	4.94	3.77

Table C.1.4.3: Base, projections and groups for summer daily average electricity and gas demand per household and per person.

Summer											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	10.32	10.01	9.99	10.16	11.37	11.60	11.33	9.40	12.68	12.13	14.02
	3.82	3.99	3.94	3.90	3.41	3.72	3.36	4.37	3.17	3.13	2.85
WD	10.21	9.89	9.88	10.04	11.25	11.48	11.22	9.27	12.59	12.00	13.91
	3.78	3.95	3.89	3.86	3.38	3.68	3.33	4.31	3.15	3.10	2.82
WE	10.63	10.32	10.30	10.47	11.67	11.92	11.63	9.71	12.90	12.45	14.29
	3.94	4.11	4.06	4.02	3.50	3.82	3.45	4.51	3.23	3.22	2.90
kWh	Totals Gdata							Groups base Gdata			
AD	3.58	3.61	3.59	3.58	3.66	3.66	3.61	3.56	3.87	3.53	3.25
	1.25	1.35	1.33	1.31	1.11	1.24	1.05	1.59	1.01	0.93	0.66
WD	3.62	3.64	3.62	3.62	3.70	3.69	3.65	3.59	3.94	3.57	3.26
	1.26	1.37	1.34	1.32	1.12	1.25	1.06	1.61	1.03	0.95	0.66
WE	3.49	3.51	3.49	3.49	3.55	3.59	3.49	3.48	3.70	3.41	3.23
	1.22	1.32	1.29	1.27	1.08	1.22	1.01	1.56	0.97	0.90	0.66

Table C.1.4.4: Base, projections and groups for autumn daily average electricity and gas demand per household and per person.

Autumn											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	11.86	11.41	11.43	11.64	13.24	13.71	13.17	10.59	14.78	14.62	17.12
	4.39	4.55	4.50	4.47	3.97	4.39	3.91	4.92	3.70	3.78	3.47
WD	11.58	11.14	11.16	11.36	12.88	13.31	12.82	10.36	14.38	14.17	16.61
	4.29	4.44	4.40	4.36	3.86	4.27	3.80	4.82	3.60	3.66	3.37
WE	12.58	12.07	12.10	12.33	14.12	14.70	14.04	11.17	15.77	15.74	18.40
	4.66	4.81	4.77	4.74	4.24	4.71	4.17	5.19	3.94	4.07	3.73
kWh	Totals Gdata							Groups base Gdata			
AD	19.52	19.50	19.47	19.48	19.92	20.03	19.60	19.21	20.64	19.53	19.91
	6.81	7.31	7.20	7.09	6.06	6.78	5.69	8.60	5.41	5.17	4.06
WD	19.20	19.17	19.14	19.15	19.60	19.69	19.29	18.87	20.29	19.28	19.68
	6.70	7.19	7.08	6.97	5.96	6.67	5.61	8.45	5.32	5.10	4.02
WE	20.27	20.28	20.23	20.23	20.67	20.82	20.32	20.00	21.47	20.12	20.45
	7.07	7.60	7.48	7.37	6.28	7.05	5.90	8.95	5.63	5.33	4.17

Table C.1.4.5: Base, projections and groups for the hottest day average electricity and gas demand per household and per person.

Hottest day											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4
WD	9.97	9.64	9.64	9.80	11.01	11.27	10.97	9.02	12.25	12.15	13.61
	3.69	3.84	3.80	3.77	3.30	3.61	3.26	4.19	3.06	3.14	2.76
WE	10.22	9.87	9.88	10.05	11.33	11.80	11.26	9.22	12.57	12.63	13.83
	3.78	3.94	3.89	3.86	3.40	3.78	3.34	4.29	3.14	3.26	2.81
kWh	Totals Gdata							Groups base Gdata			
WD	2.85	2.84	2.83	2.83	2.98	3.00	2.94	2.71	3.21	3.16	2.69
	0.99	1.06	1.05	1.03	0.91	1.02	0.85	1.21	0.84	0.84	0.55
WE	3.24	3.20	3.22	3.23	3.36	3.47	3.27	3.12	3.24	3.77	3.35
	1.13	1.20	1.19	1.17	1.02	1.18	0.95	1.40	0.85	1.00	0.68

Table C.1.4.6: Base, projections and groups for the coldest day average electricity and gas demand per household and per person.

Coldest day											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4
WD	15.28	14.85	14.81	15.06	16.59	17.21	16.50	14.03	18.43	17.50	20.65
	5.66	5.92	5.84	5.78	4.98	5.52	4.90	6.52	4.61	4.52	4.19
WE	16.79	16.33	16.29	16.55	18.23	19.02	18.11	15.47	20.05	19.09	22.57
	6.22	6.51	6.42	6.36	5.47	6.09	5.38	7.19	5.02	4.93	4.58
kWh	Totals Gdata							Groups base Gdata			
WD	61.52	61.36	61.26	61.31	62.81	65.29	61.00	60.18	65.73	62.09	63.31
	21.46	23.00	22.66	22.33	19.13	22.10	17.72	26.95	17.24	16.44	12.92
WE	64.42	64.37	64.28	64.31	65.71	69.55	63.33	63.46	67.60	65.46	64.23
	22.47	24.13	23.77	23.42	20.02	23.54	18.40	28.42	17.73	17.33	13.11

Table C.1.4.7: Base, projections and groups for the comparing seasons daily average electricity and gas demand per household and per person.

Comparing season (Autumn 2009 (Edata) and Winter 2010-11 (Gdata))											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	12.16	11.75	11.74	11.95	13.47	14.07	13.38	10.93	15.30	14.62	17.02
	4.50	4.69	4.63	4.59	4.04	4.51	3.97	5.08	3.83	3.78	3.45
WD	11.89	11.49	11.48	11.68	13.13	13.70	13.04	10.70	14.91	14.25	16.51
	4.40	4.58	4.52	4.49	3.94	4.39	3.87	4.97	3.73	3.68	3.35
WE	12.86	12.40	12.40	12.62	14.31	15.01	14.21	11.50	16.29	15.56	18.27
	4.76	4.95	4.89	4.85	4.29	4.81	4.22	5.34	4.08	4.02	3.71
kWh	Totals Gdata							Groups base Gdata			
AD	40.13	40.15	40.08	40.08	40.66	41.70	39.70	39.90	41.57	39.11	40.91
	13.99	15.05	14.82	14.59	12.37	14.12	11.54	17.87	10.90	10.35	8.35
WD	39.89	39.90	39.83	39.84	40.42	41.37	39.51	39.62	41.40	38.99	40.70
	13.91	14.96	14.73	14.51	12.30	14.00	11.48	17.74	10.86	10.32	8.31
WE	40.71	40.75	40.68	40.67	41.25	42.54	40.19	40.58	42.00	39.41	41.42
	14.20	15.28	15.04	14.81	12.56	14.40	11.68	18.17	11.01	10.43	8.45

C.1.5 Energy purchasing power

The following tables are the projections of the daily average gas demand for the variable 'Energy purchasing power' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.6.15.

Table C.1.5.1: Base, projections and groups for winter daily average electricity and gas demand per household and per person.

Winter												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	14.30	14.86	14.79	13.91	7.19	2.14	7.94	16.49	14.94	14.62	14.73	12.56
	5.29	5.10	5.18	5.45	4.32	5.16	4.19	5.16	4.97	5.08	4.70	6.05
WD	14.08	14.60	14.54	13.71	7.12	2.10	7.86	16.18	14.66	14.37	14.46	12.45
	5.21	5.01	5.09	5.37	4.27	5.06	4.15	5.06	4.88	4.99	4.61	6.00
WE	14.85	15.51	15.40	14.39	7.37	2.24	8.14	17.26	15.63	15.26	15.41	12.82
	5.49	5.33	5.40	5.64	4.44	5.40	4.30	5.40	5.20	5.30	4.91	6.18
kWh	Totals Gdata							Groups base Gdata				
AD	43.40	43.41	43.60	42.39	18.03	12.81	19.79	45.75	43.26	40.53	39.83	44.10
	15.15	14.63	14.82	14.98	12.34	14.85	11.21	14.85	14.42	13.83	13.17	18.96
WD	43.01	42.96	43.17	42.04	17.95	12.65	19.73	45.19	42.82	40.09	39.61	44.03
	15.01	14.48	14.67	14.85	12.27	14.67	11.18	14.67	14.27	13.68	13.10	18.93
WE	44.35	44.51	44.67	43.26	18.23	13.19	19.91	47.12	44.36	41.60	40.38	44.29
	15.48	15.00	15.19	15.29	12.52	15.29	11.29	15.29	14.79	14.20	13.36	19.04

Table C.1.5.2: Base, projections and groups for spring daily average electricity and gas demand per household and per person.

Spring												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	11.31	11.79	11.71	10.97	5.64	1.70	6.23	13.06	11.88	11.63	11.78	9.81
	4.18	4.05	4.11	4.30	3.39	4.08	3.29	4.08	3.95	4.04	3.76	4.73
WD	11.12	11.56	11.50	10.80	5.58	1.66	6.16	12.79	11.63	11.41	11.54	9.73
	4.11	3.97	4.03	4.23	3.35	4.00	3.26	4.00	3.87	3.96	3.68	4.69
WE	11.79	12.37	12.26	11.39	5.79	1.79	6.39	13.74	12.52	12.18	12.40	10.02
	4.36	4.25	4.30	4.46	3.49	4.30	3.37	4.30	4.17	4.23	3.96	4.83
kWh	Totals Gdata							Groups base Gdata				
AD	20.50	20.38	20.50	20.09	8.69	5.97	9.61	21.34	20.33	18.88	19.28	21.50
	7.16	6.87	6.97	7.10	5.91	6.93	5.45	6.93	6.78	6.44	6.38	9.24
WD	21.13	21.01	21.14	20.71	8.96	6.17	9.91	22.02	20.96	19.42	19.87	22.16
	7.38	7.08	7.19	7.32	6.10	7.15	5.61	7.15	6.99	6.63	6.57	9.53
WE	18.90	18.78	18.89	18.50	8.00	5.49	8.86	19.61	18.72	17.52	17.80	19.80
	6.60	6.33	6.42	6.54	5.45	6.36	5.02	6.36	6.24	5.98	5.89	8.51

Table C.1.5.3: Base, projections and groups for summer daily average electricity and gas demand per household and per person.

Summer												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	10.33	10.76	10.68	10.00	5.17	1.52	5.71	11.72	10.86	10.69	10.83	9.00
	3.82	3.69	3.74	3.92	3.10	3.67	3.02	3.67	3.61	3.71	3.45	4.34
WD	10.21	10.63	10.55	9.89	5.12	1.51	5.66	11.60	10.72	10.56	10.66	8.92
	3.78	3.65	3.70	3.88	3.07	3.63	2.99	3.63	3.57	3.67	3.40	4.30
WE	10.63	11.09	10.99	10.28	5.30	1.57	5.86	12.04	11.21	11.03	11.23	9.22
	3.93	3.81	3.85	4.03	3.18	3.77	3.09	3.77	3.73	3.83	3.58	4.44
kWh	Totals Gdata							Groups base Gdata				
AD	3.59	3.51	3.55	3.56	1.61	1.02	1.81	3.64	3.50	3.12	3.62	4.09
	1.25	1.18	1.21	1.26	1.08	1.18	1.03	1.18	1.17	1.07	1.20	1.76
WD	3.62	3.54	3.58	3.59	1.63	1.03	1.84	3.67	3.54	3.13	3.70	4.15
	1.27	1.19	1.22	1.27	1.09	1.19	1.04	1.19	1.18	1.07	1.22	1.79
WE	3.49	3.42	3.46	3.45	1.55	1.00	1.74	3.57	3.41	3.09	3.44	3.92
	1.22	1.15	1.18	1.22	1.04	1.16	0.98	1.16	1.14	1.05	1.14	1.68

Table C.1.5.4: Base, projections and groups for autumn daily average electricity and gas demand per household and per person.

Autumn												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	11.86	12.45	12.33	11.48	5.85	1.81	6.45	13.89	12.63	12.08	12.24	10.16
	4.39	4.27	4.32	4.50	3.53	4.34	3.41	4.34	4.20	4.20	3.90	4.90
WD	11.57	12.11	12.01	11.22	5.75	1.75	6.34	13.49	12.26	11.78	11.90	10.00
	4.28	4.16	4.21	4.40	3.46	4.22	3.35	4.22	4.08	4.09	3.80	4.82
WE	12.58	13.30	13.14	12.13	6.10	1.94	6.73	14.90	13.56	12.83	13.08	10.54
	4.65	4.57	4.60	4.75	3.70	4.66	3.55	4.66	4.51	4.46	4.17	5.08
kWh	Totals Gdata							Groups base Gdata				
AD	19.52	19.44	19.52	19.05	8.22	5.62	9.10	20.08	19.44	18.26	19.11	20.24
	6.81	6.55	6.64	6.73	5.59	6.52	5.16	6.52	6.48	6.23	6.32	8.70
WD	19.20	19.10	19.19	18.76	8.12	5.53	9.00	19.75	19.11	17.84	18.79	20.03
	6.70	6.44	6.52	6.63	5.52	6.41	5.10	6.41	6.37	6.09	6.22	8.61
WE	20.28	20.23	20.30	19.74	8.46	5.84	9.35	20.86	20.22	19.24	19.86	20.73
	7.08	6.82	6.90	6.97	5.76	6.77	5.30	6.77	6.74	6.56	6.57	8.91

Table C.1.5.5: Base, projections and groups for the hottest day average electricity and gas demand per household and per person.

Hottest day												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
WD	9.97	10.38	10.32	9.64	4.95	1.48	5.47	11.41	10.39	10.49	10.72	8.58
	3.69	3.56	3.62	3.77	2.98	3.57	2.89	3.57	3.46	3.64	3.42	4.13
WE	10.23	10.70	10.63	9.89	5.04	1.55	5.56	11.92	10.78	10.61	10.77	8.73
	3.78	3.68	3.72	3.87	3.04	3.73	2.94	3.73	3.59	3.68	3.43	4.21
kWh	Totals Gdata							Groups base Gdata				
AD	2.85	2.82	2.85	2.81	1.23	0.84	1.36	3.01	2.83	2.45	3.04	3.02
	0.99	0.95	0.97	0.99	0.84	0.98	0.77	0.98	0.94	0.84	1.01	1.30
WD	3.25	3.16	3.22	3.26	1.47	0.98	1.65	3.49	3.12	2.65	2.87	3.78
	1.13	1.07	1.10	1.15	1.00	1.13	0.93	1.13	1.04	0.90	0.95	1.62

Table C.1.5.6: Base, projections and groups for the coldest day average electricity and gas demand per household and per person.

Coldest day												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
WD	15.28	15.77	15.73	14.94	7.82	2.26	8.65	17.42	15.76	15.64	14.98	13.79
	5.65	5.42	5.51	5.85	4.68	5.45	4.57	5.45	5.25	5.43	4.78	6.65
WE	16.81	17.35	17.31	16.39	8.55	2.50	9.46	19.19	17.31	17.28	17.26	14.99
	6.21	5.96	6.07	6.42	5.13	6.00	4.99	6.00	5.76	6.00	5.50	7.23
kWh	Totals Gdata							Groups base Gdata				
AD	61.57	61.92	62.12	59.97	25.11	18.37	27.35	65.61	61.64	58.37	55.46	60.71
	21.49	20.87	21.12	21.19	17.28	21.29	15.50	21.29	20.55	19.92	18.35	26.10
WD	64.50	65.36	65.38	62.67	25.79	19.51	27.84	69.67	65.33	61.21	55.40	61.76
	22.51	22.03	22.22	22.14	17.85	22.61	15.78	22.61	21.78	20.89	18.32	26.55

Table C.1.5.7: Base, projections and groups for the comparing seasons daily average electricity and gas demand per household and per person.

Comparing season (Autumn 2009 (Edata) and Winter 2010-11 (Gdata))												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	12.17	12.73	12.64	11.80	6.03	1.85	6.65	14.26	12.85	12.43	12.53	10.49
	4.50	4.37	4.43	4.62	3.64	4.46	3.51	4.46	4.27	4.32	4.00	5.05
WD	11.89	12.40	12.33	11.55	5.93	1.81	6.55	13.89	12.48	12.13	12.21	10.34
	4.40	4.26	4.32	4.52	3.57	4.34	3.46	4.34	4.15	4.21	3.89	4.98
WE	12.86	13.55	13.41	12.42	6.28	1.98	6.92	15.21	13.75	13.16	13.33	10.86
	4.76	4.65	4.70	4.87	3.80	4.76	3.65	4.76	4.58	4.57	4.25	5.24
kWh	Totals Gdata							Groups base Gdata				
AD	40.15	40.16	40.24	39.17	16.77	11.70	18.48	41.77	40.28	37.33	36.17	41.35
	14.01	13.53	13.68	13.84	11.44	13.56	10.47	13.56	13.43	12.74	11.96	17.78
WD	39.90	39.90	39.98	38.94	16.69	11.61	18.41	41.46	40.02	37.08	36.19	41.18
	13.93	13.44	13.59	13.76	11.38	13.46	10.43	13.46	13.34	12.65	11.97	17.71
WE	40.74	40.81	40.87	39.74	16.95	11.91	18.65	42.53	40.92	37.97	36.14	41.75
	14.22	13.75	13.89	14.04	11.58	13.80	10.57	13.80	13.64	12.96	11.95	17.95

C.1.6 Space heating

The following tables are the projections of the daily average gas demand for the variable 'Space heating' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.7.6.

Table C.1.6.1: Base, projections and groups for winter daily average electricity demand per household and per person.

Winter									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	13.10	13.95	14.65	13.68	13.02	15.06	12.72	16.68	12.84
	5.05	5.40	5.69	5.29	5.07	4.96	5.08	6.55	4.94
WD	12.93	13.81	14.53	13.54	12.85	14.83	12.56	16.63	12.67
	4.99	5.35	5.64	5.23	5.00	4.89	5.02	6.53	4.88
WE	13.51	14.30	14.94	14.05	13.44	15.63	13.11	16.82	13.27
	5.21	5.54	5.80	5.43	5.23	5.15	5.24	6.61	5.11

Table C.1.6.2: Base, projections and groups for spring daily average electricity demand per household and per person.

Spring									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	10.52	10.88	11.17	10.76	10.48	12.34	10.20	12.02	10.41
	4.06	4.21	4.34	4.16	4.07	4.07	4.08	4.72	4.01
WD	10.39	10.78	11.10	10.66	10.36	12.19	10.08	12.03	10.27
	4.01	4.18	4.31	4.12	4.03	4.02	4.03	4.73	3.96
WE	10.84	11.11	11.33	11.02	10.79	12.72	10.50	11.99	10.75
	4.18	4.30	4.40	4.26	4.20	4.19	4.20	4.71	4.14

Table C.1.6.3: Base, projections and groups for summer daily average electricity demand per household and per person.

Summer									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	9.42	9.48	9.53	9.46	9.42	10.89	9.20	9.67	9.40
	3.63	3.67	3.70	3.66	3.66	3.59	3.68	3.80	3.62
WD	9.35	9.41	9.47	9.39	9.34	10.84	9.12	9.64	9.32
	3.60	3.65	3.68	3.63	3.63	3.57	3.64	3.78	3.59
WE	9.62	9.65	9.68	9.64	9.61	11.01	9.40	9.77	9.61
	3.71	3.74	3.76	3.73	3.74	3.63	3.76	3.83	3.70

Table C.1.6.4: Base, projections and groups for autumn daily average electricity demand per household and per person.

Autumn									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	11.10	11.37	11.58	11.29	11.06	13.09	10.76	12.21	11.02
	4.28	4.40	4.50	4.36	4.30	4.32	4.30	4.80	4.24
WD	10.86	11.14	11.36	11.05	10.82	12.81	10.53	12.02	10.78
	4.19	4.31	4.41	4.27	4.21	4.22	4.21	4.72	4.15
WE	11.71	11.95	12.13	11.87	11.66	13.82	11.34	12.69	11.64
	4.51	4.62	4.71	4.59	4.53	4.55	4.53	4.98	4.48

Table C.1.6.5: Base, projections and groups for the hottest day average electricity demand per household and per person.

Hottest day									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
AD	9.26	9.30	9.33	9.29	9.21	10.89	8.96	9.43	9.25
	3.57	3.60	3.63	3.59	3.58	3.59	3.58	3.70	3.56
WD	9.32	9.27	9.23	9.29	9.33	10.95	9.09	9.12	9.33
	3.59	3.59	3.59	3.59	3.63	3.61	3.63	3.58	3.59

Table C.1.6.6: Base, projections and groups for the coldest day average electricity demand per household and per person.

Coldest day									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
AD	13.84	15.35	16.57	14.87	13.66	15.67	13.36	20.16	13.38
	5.33	5.94	6.44	5.75	5.32	5.17	5.34	7.92	5.15
WD	14.94	16.64	18.01	16.10	14.84	17.11	14.50	22.07	14.42
	5.76	6.44	7.00	6.23	5.77	5.64	5.79	8.67	5.55

Table C.1.6.7: Base, projections and groups for the comparing season daily average electricity demand per household and per person.

Comparing season (Autumn 2009)									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
AD	11.22	11.45	11.63	11.38	11.17	13.23	10.87	12.18	11.15
	4.33	4.43	4.52	4.40	4.34	4.36	4.34	4.78	4.29
WD	11.01	11.25	11.44	11.17	10.97	12.97	10.67	12.00	10.94
	4.24	4.35	4.44	4.32	4.27	4.27	4.26	4.71	4.21
WE	11.74	11.95	12.12	11.89	11.69	13.88	11.36	12.63	11.68
	4.53	4.63	4.71	4.60	4.54	4.57	4.54	4.96	4.50

C.1.7 Type of building

The following tables are the projections of the daily average gas demand for the variable 'Type of building' for winter, spring, summer, autumn, and the hottest and coldest days.

They complement the projections from table 6.5.8.3.

Table C.1.7.1: Base, projections and groups for winter daily average electricity and gas demand per household and per person.

Winter											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	14.30	13.29	13.29	14.30	13.57	16.76	13.09	7.86	13.27	15.69	11.95
	5.29	5.28	5.28	5.30	5.24	5.17	5.25	5.18	5.06	5.47	5.03
WD	14.08	13.09	13.09	14.08	13.36	16.44	12.90	7.75	13.09	15.43	11.78
	5.21	5.20	5.20	5.22	5.16	5.07	5.18	5.11	4.99	5.38	4.96
WE	14.84	13.79	13.79	14.85	14.08	17.54	13.56	8.13	13.74	16.31	12.37
	5.49	5.48	5.48	5.51	5.44	5.41	5.44	5.36	5.24	5.69	5.21
kWh	Totals Gdata							Groups base Gdata			
AD	43.38	39.33	39.45	44.20	42.24	47.50	39.64	20.02	43.26	50.94	38.41
	15.12	14.98	14.99	15.21	15.24	15.01	15.12	14.01	14.73	16.76	14.43
WD	43.00	38.96	39.07	43.81	41.84	46.95	39.31	19.60	42.89	50.49	38.11
	14.99	14.83	14.85	15.07	15.10	14.84	14.99	13.72	14.61	16.61	14.31
WE	44.30	40.27	40.38	45.17	43.21	48.87	40.45	21.04	44.18	52.04	39.16
	15.45	15.33	15.34	15.54	15.59	15.44	15.43	14.73	15.05	17.12	14.71

Table C.1.7.2: Base, projections and groups for spring daily average electricity and gas demand per household and per person.

Spring											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	11.31	10.54	10.54	11.30	10.80	13.26	10.43	6.36	10.67	12.25	9.70
	4.19	4.19	4.19	4.19	4.17	4.09	4.19	4.19	4.07	4.27	4.09
WD	11.12	10.37	10.37	11.11	10.62	12.98	10.27	6.29	10.52	12.01	9.58
	4.12	4.12	4.12	4.12	4.11	4.00	4.12	4.15	4.01	4.19	4.03
WE	11.79	10.97	10.97	11.79	11.24	13.95	10.83	6.52	11.05	12.84	10.02
	4.36	4.36	4.36	4.37	4.34	4.30	4.35	4.30	4.21	4.47	4.22
kWh	Totals Gdata							Groups base Gdata			
AD	20.49	18.65	18.75	20.80	20.00	22.00	18.96	9.71	20.22	23.65	19.12
	7.14	7.10	7.12	7.15	7.23	6.95	7.23	6.80	6.89	7.78	7.18
WD	21.13	19.23	19.32	21.45	20.60	22.70	19.52	9.99	20.88	24.35	19.65
	7.37	7.32	7.34	7.38	7.44	7.17	7.44	6.99	7.11	8.01	7.38
WE	18.88	17.20	17.30	19.16	18.47	20.23	17.55	9.00	18.53	21.88	17.77
	6.58	6.55	6.57	6.59	6.68	6.39	6.69	6.30	6.31	7.20	6.67

Table C.1.7.3: Base, projections and groups for summer daily average electricity and gas demand per household and per person.

Summer											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	10.33	9.63	9.63	10.32	9.89	11.92	9.58	5.88	9.72	11.20	8.83
	3.82	3.83	3.83	3.83	3.82	3.68	3.84	3.87	3.71	3.90	3.72
WD	10.21	9.52	9.52	10.21	9.78	11.80	9.47	5.83	9.64	11.05	8.73
	3.78	3.79	3.78	3.78	3.78	3.64	3.80	3.84	3.68	3.85	3.68
WE	10.63	9.91	9.92	10.62	10.17	12.23	9.86	6.01	9.93	11.57	9.10
	3.93	3.94	3.94	3.94	3.93	3.77	3.96	3.96	3.78	4.03	3.83
kWh	Totals Gdata							Groups base Gdata			
AD	3.58	3.37	3.40	3.60	3.57	3.72	3.46	2.29	3.43	3.87	3.81
	1.25	1.28	1.29	1.24	1.29	1.18	1.32	1.60	1.17	1.27	1.43
WD	3.61	3.41	3.44	3.64	3.61	3.75	3.50	2.35	3.46	3.92	3.83
	1.26	1.30	1.31	1.25	1.31	1.19	1.34	1.64	1.18	1.29	1.44
WE	3.49	3.27	3.30	3.50	3.47	3.65	3.36	2.14	3.34	3.74	3.75
	1.22	1.25	1.25	1.21	1.26	1.15	1.28	1.50	1.14	1.23	1.41

Table C.1.7.4: Base, projections and groups for autumn daily average electricity and gas demand per household and per person.

Autumn											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	11.86	11.05	11.05	11.86	11.32	14.11	10.91	6.69	11.21	12.86	10.09
	4.39	4.39	4.39	4.40	4.37	4.35	4.38	4.41	4.27	4.48	4.25
WD	11.57	10.78	10.78	11.57	11.05	13.70	10.65	6.52	10.96	12.53	9.86
	4.28	4.29	4.28	4.29	4.27	4.22	4.27	4.29	4.18	4.37	4.15
WE	12.58	11.73	11.73	12.58	12.01	15.14	11.54	7.12	11.83	13.67	10.67
	4.66	4.66	4.66	4.67	4.63	4.67	4.63	4.69	4.51	4.77	4.49
kWh	Totals Gdata							Groups base Gdata			
AD	19.52	17.77	17.84	19.85	19.01	20.77	18.07	9.39	19.33	22.74	17.76
	6.80	6.77	6.78	6.83	6.87	6.57	6.89	6.57	6.59	7.48	6.67
WD	19.20	17.48	17.55	19.53	18.69	20.43	17.76	9.26	19.00	22.41	17.45
	6.69	6.66	6.67	6.72	6.75	6.46	6.78	6.48	6.47	7.37	6.55
WE	20.27	18.45	18.52	20.61	19.76	21.58	18.78	9.68	20.11	23.52	18.47
	7.07	7.02	7.04	7.09	7.14	6.82	7.16	6.78	6.85	7.74	6.94

Table C.1.7.5: Base, projections and groups for the hottest day average electricity demand per household and per person.

Hottest day											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
WD	9.98	9.31	9.32	9.96	9.57	11.59	9.27	5.73	9.50	10.72	8.67
	3.69	3.70	3.70	3.70	3.70	3.57	3.72	3.78	3.62	3.74	3.65
WE	10.22	9.48	9.48	10.21	9.75	12.09	9.41	5.44	9.62	11.09	8.77
	3.78	3.77	3.77	3.79	3.77	3.73	3.77	3.59	3.67	3.87	3.69
kWh	Totals Gdata							Groups base Gdata			
WD	2.85	2.74	2.76	2.87	2.87	3.06	2.75	2.16	2.70	3.08	3.09
	0.99	1.04	1.05	0.99	1.04	0.97	1.05	1.51	0.92	1.01	1.16
WE	3.24	3.08	3.11	3.27	3.27	3.59	3.11	2.23	3.08	3.57	3.44
	1.13	1.17	1.18	1.13	1.18	1.13	1.18	1.56	1.05	1.18	1.29

Table C.1.7.6: Base, projections and groups for the coldest day average electricity demand per household and per person.

Coldest day											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
WD	15.28	14.40	14.39	15.32	14.58	17.76	14.11	9.61	14.09	16.79	12.74
	5.66	5.72	5.72	5.68	5.64	5.48	5.66	6.33	5.37	5.85	5.37
WE	16.78	16.00	15.97	16.88	16.04	19.52	15.52	11.79	15.31	18.60	13.61
	6.21	6.36	6.35	6.26	6.20	6.02	6.23	7.77	5.84	6.48	5.73
kWh	Totals Gdata							Groups base Gdata			
WD	61.50	55.78	55.89	62.72	59.87	68.25	55.83	28.52	61.85	71.64	53.68
	21.44	21.24	21.24	21.58	21.58	21.57	21.29	19.96	21.07	23.57	20.16
WE	64.40	59.10	59.23	65.76	62.98	72.01	58.65	34.10	64.07	75.76	56.83
	22.45	22.50	22.50	22.62	22.70	22.76	22.37	23.87	21.82	24.92	21.34

Table C.1.7.7: Base, projections and groups for the comparing seasons daily average electricity and gas demand per household and per person.

Comparing season (Autumn 2009 (Edata) and Winter 2010-11 (Gdata))											
kWh	Totals Edata							Groups base Edata			
	base	NSP	PR	MF	FW			G1	G2	G3	G4
					All	FWr	FWp				
AD	12.17	11.29	11.29	12.16	11.59	14.51	11.15	6.54	11.40	13.27	10.27
	4.50	4.49	4.49	4.51	4.47	4.47	4.47	4.31	4.35	4.63	4.33
WD	11.89	11.03	11.03	11.88	11.33	14.12	10.91	6.39	11.16	12.94	10.08
	4.40	4.38	4.38	4.41	4.38	4.35	4.38	4.21	4.25	4.51	4.25
WE	12.86	11.93	11.93	12.87	12.23	15.47	11.75	6.92	12.01	14.09	10.74
	4.76	4.74	4.74	4.77	4.72	4.77	4.71	4.56	4.58	4.91	4.52
kWh	Totals Gdata							Groups base Gdata			
AD	40.11	36.49	36.61	40.87	39.05	43.21	36.93	19.20	39.74	47.37	35.85
	13.99	13.89	13.91	14.06	14.10	13.65	14.08	13.44	13.54	15.58	13.46
WD	39.87	36.29	36.42	40.63	38.82	42.89	36.73	19.21	39.50	47.08	35.64
	13.90	13.82	13.84	13.98	14.02	13.55	14.01	13.45	13.46	15.49	13.38
WE	40.69	36.97	37.09	41.46	39.62	43.98	37.41	19.16	40.33	48.07	36.35
	14.19	14.07	14.09	14.26	14.31	13.90	14.27	13.42	13.74	15.81	13.65

C.1.8 Number of bedrooms

The following tables are the projections of the daily average gas demand for the variable 'Number of bedrooms' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.9.4.

Table C.1.8.1: Base, projections and groups for winter daily average electricity and gas demand per household and per person.

Winter												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	14.29	14.10	12.29	13.83	10.08	21.42	8.38	9.36	9.30	12.58	16.10	19.61
	5.29	5.04	5.14	5.56	4.86	6.86	4.57	8.27	5.33	5.21	5.22	5.61
WD	14.07	13.88	12.11	13.64	9.94	21.04	8.28	9.32	9.18	12.41	15.81	19.32
	5.21	4.96	5.07	5.48	4.80	6.74	4.51	8.24	5.26	5.14	5.12	5.52
WE	14.83	14.64	12.72	14.32	10.43	22.36	8.65	9.47	9.59	13.01	16.79	20.34
	5.49	5.23	5.32	5.76	5.03	7.16	4.71	8.37	5.50	5.39	5.44	5.81
kWh	Totals Gdata							Groups base Gdata				
AD	43.38	42.93	36.08	40.60	34.55	60.64	24.07	15.56	31.41	38.45	51.62	62.17
	15.13	14.41	14.32	15.54	14.58	19.36	12.54	14.53	17.10	14.07	16.18	15.49
WD	43.01	42.56	35.77	40.28	34.22	59.96	23.89	15.47	31.17	38.15	51.08	61.86
	15.00	14.29	14.20	15.42	14.44	19.15	12.44	14.44	16.97	13.96	16.01	15.41
WE	44.31	43.83	36.83	41.38	35.35	62.31	24.53	15.79	31.99	39.22	52.94	62.93
	15.45	14.72	14.62	15.84	14.90	19.90	12.78	14.73	17.42	14.35	16.59	15.68

Table C.1.8.2: Base, projections and groups for spring daily average electricity and gas demand per household and per person.

Spring												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	11.30	11.15	9.67	10.80	7.96	16.78	6.65	6.74	7.39	10.01	12.77	15.23
	4.19	3.98	4.05	4.34	3.85	5.37	3.62	5.96	4.23	4.15	4.14	4.35
WD	11.12	10.95	9.53	10.63	7.86	16.44	6.58	6.74	7.32	9.87	12.53	14.90
	4.12	3.91	3.99	4.28	3.80	5.26	3.58	5.96	4.19	4.09	4.06	4.26
WE	11.79	11.64	10.03	11.24	8.23	17.65	6.82	6.75	7.56	10.38	13.38	16.06
	4.36	4.16	4.20	4.52	3.97	5.65	3.71	5.96	4.33	4.30	4.33	4.59
kWh	Totals Gdata							Groups base Gdata				
AD	20.50	20.20	17.31	19.45	16.72	28.26	12.06	8.62	16.03	18.16	24.19	28.63
	7.15	6.78	6.87	7.45	7.11	9.02	6.28	8.05	8.73	6.64	7.58	7.14
WD	21.13	20.82	17.86	20.07	17.24	29.20	12.42	8.92	16.60	18.74	24.89	29.54
	7.37	6.99	7.09	7.68	7.33	9.32	6.47	8.33	9.04	6.86	7.80	7.36
WE	18.89	18.62	15.92	17.89	15.39	25.88	11.16	7.86	14.58	16.70	22.40	26.33
	6.59	6.25	6.32	6.85	6.56	8.27	5.81	7.34	7.94	6.11	7.02	6.56

Table C.1.8.3: Base, projections and groups for summer daily average electricity and gas demand per household and per person.

Summer												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	10.33	10.19	8.79	9.80	7.20	15.04	6.03	5.77	6.63	9.14	11.70	13.96
	3.82	3.64	3.68	3.94	3.48	4.82	3.29	5.10	3.80	3.78	3.79	3.99
WD	10.21	10.07	8.69	9.69	7.12	14.88	5.97	5.71	6.57	9.04	11.56	13.76
	3.78	3.60	3.64	3.90	3.45	4.76	3.25	5.05	3.76	3.74	3.75	3.93
WE	10.63	10.49	9.04	10.10	7.40	15.46	6.20	5.92	6.81	9.39	12.04	14.45
	3.94	3.75	3.78	4.06	3.58	4.95	3.38	5.23	3.90	3.89	3.90	4.13
kWh	Totals Gdata							Groups base Gdata				
AD	3.58	3.50	3.17	3.56	3.18	4.91	2.48	2.46	3.20	3.20	4.09	4.76
	1.25	1.17	1.26	1.36	1.38	1.57	1.29	2.30	1.74	1.17	1.28	1.19
WD	3.62	3.53	3.19	3.60	3.20	4.98	2.48	2.41	3.25	3.22	4.15	4.84
	1.26	1.19	1.27	1.38	1.39	1.59	1.29	2.25	1.77	1.18	1.30	1.21
WE	3.49	3.40	3.11	3.48	3.13	4.73	2.47	2.59	3.08	3.15	3.95	4.58
	1.22	1.14	1.23	1.33	1.36	1.51	1.29	2.42	1.68	1.15	1.24	1.14

Table C.1.8.4: Base, projections and groups for autumn daily average electricity and gas demand per household and per person.

Autumn												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	11.86	11.70	10.11	11.31	8.33	17.86	6.90	6.82	7.72	10.43	13.47	16.04
	4.39	4.18	4.23	4.55	4.01	5.72	3.76	6.03	4.42	4.32	4.37	4.58
WD	11.57	11.41	9.88	11.05	8.15	17.34	6.78	6.74	7.58	10.20	13.12	15.61
	4.28	4.08	4.14	4.44	3.93	5.55	3.69	5.96	4.34	4.22	4.25	4.46
WE	12.57	12.42	10.68	11.97	8.77	19.15	7.22	7.02	8.06	11.02	14.33	17.13
	4.66	4.44	4.47	4.81	4.22	6.13	3.93	6.21	4.62	4.56	4.65	4.90
kWh	Totals Gdata							Groups base Gdata				
AD	19.52	19.23	16.42	18.38	15.72	26.53	11.36	7.59	15.15	17.34	23.04	27.07
	6.81	6.46	6.52	7.04	6.69	8.47	5.92	7.08	8.25	6.35	7.22	6.75
WD	19.20	18.91	16.17	18.13	15.50	26.14	11.20	7.59	14.99	17.03	22.64	26.79
	6.70	6.35	6.42	6.94	6.60	8.35	5.84	7.08	8.16	6.23	7.10	6.68
WE	20.27	19.96	17.02	18.96	16.25	27.43	11.74	7.59	15.53	18.07	23.96	27.74
	7.07	6.70	6.75	7.26	6.92	8.76	6.12	7.09	8.45	6.61	7.51	6.91

Table C.1.8.5: Base, projections and groups for the hottest day average electricity demand per household and per person.

Hottest day												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
WD	9.97	9.83	8.54	9.50	7.05	14.53	5.94	6.06	6.37	8.84	11.39	13.12
	3.69	3.51	3.58	3.82	3.42	4.65	3.23	5.35	3.65	3.66	3.69	3.75
WE	10.22	10.09	8.61	9.55	6.97	15.17	5.75	4.93	6.42	9.02	11.72	13.66
	3.78	3.60	3.60	3.84	3.36	4.86	3.13	4.35	3.68	3.73	3.80	3.90
kWh	Totals Gdata							Groups base Gdata				
WD	2.85	2.81	2.52	2.94	2.55	4.17	1.89	2.24	2.42	2.53	3.19	4.46
	0.99	0.94	1.00	1.13	1.09	1.33	0.99	2.09	1.32	0.93	1.00	1.11
WE	3.25	3.19	2.83	3.25	2.90	4.71	2.16	2.01	2.84	2.88	3.67	4.82
	1.13	1.07	1.12	1.24	1.24	1.50	1.13	1.88	1.54	1.05	1.15	1.20

Table C.1.8.6: Base, projections and groups for the coldest day average electricity demand per household and per person.

Coldest day												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
WD	15.26	15.00	13.32	14.93	11.09	22.80	9.35	11.05	10.56	13.62	16.92	20.51
	5.65	5.36	5.57	6.00	5.38	7.30	5.09	9.77	6.05	5.64	5.48	5.86
WE	16.77	16.50	14.58	16.36	12.02	25.34	10.03	11.69	11.67	14.75	18.97	22.24
	6.21	5.89	6.10	6.58	5.81	8.11	5.46	10.33	6.69	6.11	6.15	6.36
kWh	Totals Gdata							Groups base Gdata				
WD	61.50	60.93	50.94	57.27	48.55	86.44	33.35	22.24	42.76	54.27	74.17	87.09
	21.45	20.46	20.22	21.93	20.41	27.60	17.37	20.76	23.28	19.85	23.24	21.70
WE	64.40	63.83	53.26	60.06	50.66	91.54	34.29	22.21	45.30	56.75	77.42	92.71
	22.46	21.43	21.14	23.00	21.22	29.23	17.86	20.73	24.67	20.76	24.26	23.10

Table C.1.8.7: Base, projections and groups for the comparing seasons daily average electricity and gas demand per household and per person.

Comparing season (Autumn 2009 (Edata) and Winter 2010-11 (Gdata))												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	12.16	12.02	10.32	11.55	8.42	18.27	6.95	6.80	7.63	10.69	13.86	16.60
	4.50	4.29	4.32	4.65	4.05	5.85	3.78	6.01	4.37	4.43	4.49	4.74
WD	11.88	11.74	10.09	11.29	8.24	17.79	6.81	6.71	7.47	10.48	13.51	16.15
	4.40	4.19	4.23	4.54	3.97	5.69	3.71	5.93	4.28	4.34	4.38	4.62
WE	12.86	12.72	10.87	12.22	8.87	19.49	7.28	7.02	8.04	11.22	14.71	17.72
	4.76	4.54	4.55	4.91	4.26	6.24	3.96	6.21	4.60	4.64	4.77	5.06
kWh	Totals Gdata							Groups base Gdata				
AD	40.11	39.69	33.48	37.94	32.29	55.54	22.93	15.07	30.02	35.32	47.62	58.57
	13.99	13.33	13.28	14.52	13.68	17.73	11.94	14.06	16.34	12.92	14.92	14.60
WD	39.87	39.44	33.30	37.72	32.10	55.09	22.84	15.00	30.00	35.12	47.31	58.04
	13.91	13.24	13.22	14.44	13.61	17.59	11.90	14.00	16.34	12.85	14.83	14.46
WE	40.69	40.30	33.90	38.48	32.75	56.63	23.14	15.23	30.05	35.79	48.39	59.87
	14.19	13.53	13.45	14.73	13.86	18.08	12.06	14.21	16.37	13.09	15.16	14.92

C.1.9 Appliances ownership and use

The following tables are the projections of the daily average gas demand for the variable 'Appliances ownership and use' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.10.4.

Table C.1.9.1: Base, projections and groups for winter daily average electricity demand per household and per person.

Winter												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	14.30	10.42	14.01	15.64	9.56	17.75	8.34	8.05	11.89	16.33	20.18	22.14
	5.29	5.34	5.31	5.26	5.20	5.19	5.21	5.24	5.50	5.18	5.22	5.12
WD	14.08	10.26	13.79	15.40	9.44	17.42	8.24	7.95	11.70	16.08	19.87	21.83
	5.21	5.27	5.23	5.18	5.14	5.09	5.15	5.17	5.42	5.10	5.15	5.04
WE	14.84	10.79	14.54	16.23	9.88	18.58	8.58	8.29	12.36	16.96	20.94	22.90
	5.50	5.53	5.51	5.46	5.36	5.43	5.35	5.40	5.72	5.38	5.42	5.29

Table C.1.9.2: Base, projections and groups for spring daily average electricity demand per household and per person.

Spring												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	11.31	8.08	11.07	12.43	7.38	14.08	6.38	6.11	9.32	13.08	15.91	17.88
	4.19	4.15	4.20	4.18	4.00	4.11	3.98	3.97	4.31	4.15	4.12	4.13
WD	11.12	7.99	10.89	12.21	7.30	13.79	6.33	6.07	9.18	12.84	15.59	17.54
	4.12	4.10	4.13	4.10	3.96	4.03	3.95	3.95	4.25	4.07	4.04	4.05
WE	11.79	8.33	11.54	12.98	7.57	14.82	6.49	6.21	9.66	13.69	16.71	18.74
	4.37	4.28	4.37	4.36	4.09	4.33	4.05	4.04	4.47	4.34	4.33	4.33

Table C.1.9.3: Base, projections and groups for summer daily average electricity demand per household and per person.

Summer												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	10.32	7.26	10.11	11.37	6.56	12.62	5.65	5.35	8.48	12.00	14.66	16.37
	3.82	3.73	3.83	3.82	3.55	3.69	3.53	3.48	3.93	3.81	3.80	3.78
WD	10.21	7.18	9.99	11.25	6.50	12.50	5.61	5.31	8.36	11.87	14.51	16.30
	3.78	3.68	3.79	3.78	3.52	3.65	3.50	3.45	3.87	3.76	3.76	3.77
WE	10.63	7.47	10.42	11.69	6.70	12.93	5.76	5.45	8.79	12.34	15.06	16.56
	3.94	3.83	3.95	3.93	3.62	3.78	3.60	3.54	4.07	3.91	3.90	3.83

Table C.1.9.4: Base, projections and groups for autumn daily average electricity demand per household and per person.

Autumn												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5
					All	FWr	FWp					
AD	11.86	8.42	11.61	13.05	7.68	14.95	6.59	6.31	9.73	13.74	16.91	18.65
	4.39	4.32	4.40	4.39	4.15	4.37	4.11	4.11	4.51	4.36	4.38	4.31
WD	11.58	8.24	11.33	12.73	7.53	14.53	6.49	6.20	9.51	13.40	16.46	18.21
	4.29	4.23	4.30	4.28	4.07	4.24	4.05	4.04	4.40	4.25	4.26	4.21
WE	12.58	8.86	12.31	13.85	8.04	16.00	6.85	6.58	10.30	14.61	18.06	19.75
	4.66	4.55	4.67	4.66	4.33	4.68	4.28	4.28	4.77	4.63	4.67	4.56

Table C.1.9.5: Base, projections and groups for the hottest day average electricity demand per household and per person.

Hottest day												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
WD	9.97	6.99	9.75	11.02	6.40	12.35	5.51	5.20	8.07	11.68	14.17	16.19
	3.69	3.59	3.70	3.70	3.46	3.61	3.44	3.38	3.74	3.70	3.67	3.74
WE	10.22	7.04	10.02	11.27	6.30	12.92	5.31	4.97	8.42	11.98	14.58	15.81
	3.78	3.61	3.80	3.79	3.37	3.78	3.31	3.23	3.90	3.80	3.77	3.65

Table C.1.9.6: Base, projections and groups for the coldest day average electricity demand per household and per person.

Coldest day												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
WD	15.28	11.36	15.02	16.60	10.58	18.74	9.36	8.97	12.79	17.62	21.10	21.94
	5.66	5.83	5.69	5.58	5.79	5.47	5.84	5.84	5.92	5.59	5.46	5.07
WE	16.79	12.76	16.52	18.13	11.83	20.46	10.54	10.26	14.33	19.00	23.03	23.55
	6.22	6.55	6.26	6.09	6.50	5.98	6.58	6.67	6.63	6.03	5.96	5.44

Table C.1.9.7: Base, projections and groups for the comparing season daily average electricity demand per household and per person.

Comparing season (Autumn 2009)												
kWh	Totals Edata							Groups base Edata				
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5
AD	12.16	8.58	11.91	13.39	7.79	15.38	6.65	6.37	9.98	14.06	17.55	19.12
	4.50	4.40	4.51	4.50	4.20	4.49	4.15	4.14	4.62	4.46	4.54	4.42
WD	11.89	8.41	11.64	13.07	7.65	14.98	6.56	6.27	9.76	13.73	17.08	18.64
	4.40	4.32	4.41	4.39	4.13	4.38	4.09	4.08	4.52	4.36	4.42	4.31
WE	12.86	9.00	12.58	14.18	8.12	16.40	6.89	6.61	10.53	14.87	18.71	20.30
	4.76	4.62	4.77	4.76	4.36	4.79	4.30	4.30	4.87	4.72	4.84	4.69

C.1.10 Energy poverty

The following tables are the projections of the daily average gas demand for the variable 'Energy poverty' for winter, spring, summer, autumn, and the hottest and coldest days.

They complement the projections from table 6.5.11.3.

Table C.1.10.1: Base, projections and groups for winter daily average electricity and gas demand per household and per person.

Winter									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	14.30	14.23	14.24	14.30	14.95	16.50	14.72	14.90	14.23
	5.29	5.27	5.27	5.30	5.59	5.17	5.65	5.57	5.27
WD	14.08	14.01	14.02	14.08	14.72	16.19	14.50	14.67	14.01
	5.21	5.18	5.19	5.21	5.50	5.07	5.56	5.48	5.18
WE	14.84	14.77	14.78	14.84	15.53	17.27	15.27	15.48	14.77
	5.50	5.46	5.47	5.50	5.80	5.41	5.86	5.78	5.46
kWh	Totals Gdata							Groups base	
AD	43.39	43.45	43.44	43.39	43.61	45.61	42.25	42.84	43.45
	15.13	15.18	15.18	15.13	14.57	14.70	14.33	14.68	15.18
WD	43.01	43.09	43.08	43.02	43.11	45.08	41.76	42.31	43.09
	15.00	15.05	15.05	15.00	14.40	14.52	14.16	14.50	15.05
WE	44.31	44.33	44.33	44.31	44.85	46.93	43.44	44.14	44.33
	15.45	15.49	15.49	15.46	14.99	15.12	14.73	15.13	15.49

Table C.1.10.2: Base, projections and groups for spring daily average electricity and gas demand per household and per person.

Spring									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	11.31	11.27	11.27	11.31	11.76	13.08	11.56	11.68	11.27
	4.19	4.17	4.17	4.19	4.39	4.09	4.44	4.36	4.17
WD	11.12	11.08	11.08	11.12	11.58	12.81	11.39	11.50	11.08
	4.12	4.10	4.10	4.12	4.33	4.01	4.37	4.30	4.10
WE	11.79	11.75	11.75	11.79	12.21	13.76	11.98	12.12	11.75
	4.37	4.35	4.35	4.37	4.56	4.31	4.60	4.53	4.35
kWh	Totals Gdata							Groups base	
AD	20.50	20.51	20.51	20.50	20.83	21.30	20.36	20.41	20.51
	7.15	7.17	7.16	7.15	6.96	6.86	6.91	6.99	7.17
WD	21.13	21.14	21.14	21.13	21.46	21.98	20.97	21.04	21.14
	7.37	7.39	7.39	7.37	7.17	7.08	7.11	7.21	7.39
WE	18.89	18.89	18.89	18.89	19.23	19.57	18.83	18.83	18.89
	6.59	6.60	6.60	6.59	6.43	6.31	6.38	6.45	6.60

Table C.1.10.3: Base, projections and groups for summer daily average electricity and gas demand per household and per person.

Summer									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
AD	10.32	10.31	10.31	10.32	10.57	11.74	10.39	10.49	10.31
	3.82	3.81	3.81	3.82	3.95	3.68	3.99	3.92	3.81
WD	10.21	10.19	10.19	10.21	10.44	11.62	10.27	10.36	10.19
	3.78	3.77	3.77	3.78	3.90	3.64	3.94	3.87	3.77
WE	10.63	10.61	10.61	10.63	10.88	12.05	10.70	10.80	10.61
	3.94	3.92	3.93	3.94	4.06	3.77	4.11	4.03	3.92
kWh	Totals Gdata							Groups base	
AD	3.58	3.55	3.56	3.58	3.73	3.59	3.73	3.83	3.55
	1.25	1.24	1.24	1.25	1.25	1.16	1.26	1.31	1.24
WD	3.62	3.59	3.59	3.62	3.75	3.61	3.75	3.86	3.59
	1.26	1.25	1.26	1.26	1.25	1.16	1.27	1.32	1.25
WE	3.49	3.46	3.46	3.49	3.67	3.53	3.68	3.74	3.46
	1.22	1.21	1.21	1.22	1.23	1.14	1.25	1.28	1.21

Table C.1.10.4: Base, projections and groups for autumn daily average electricity and gas demand per household and per person.

Autumn									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
AD	11.86	11.85	11.85	11.86	12.13	13.93	11.86	12.02	11.85
	4.39	4.38	4.38	4.39	4.53	4.36	4.55	4.49	4.38
WD	11.58	11.56	11.56	11.58	11.83	13.53	11.57	11.71	11.56
	4.29	4.28	4.28	4.29	4.41	4.24	4.44	4.37	4.28
WE	12.58	12.56	12.56	12.58	12.90	14.94	12.60	12.80	12.56
	4.66	4.65	4.65	4.66	4.81	4.68	4.83	4.78	4.65
kWh	Totals Gdata							Groups base	
AD	19.52	19.56	19.56	19.53	19.25	19.96	18.71	19.16	19.56
	6.81	6.84	6.83	6.81	6.43	6.43	6.35	6.56	6.84
WD	19.20	19.23	19.23	19.21	18.97	19.62	18.46	18.91	19.23
	6.70	6.72	6.72	6.70	6.34	6.32	6.26	6.48	6.72
WE	20.27	20.33	20.33	20.28	19.91	20.75	19.31	19.72	20.33
	7.07	7.10	7.10	7.07	6.65	6.69	6.55	6.76	7.10

Table C.1.10.5: Base, projections and groups for the hottest day average electricity demand per household and per person.

Hottest day									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
WD	9.97	9.97	9.97	9.97	10.11	11.43	9.91	10.02	9.97
	3.69	3.69	3.69	3.69	3.77	3.58	3.80	3.74	3.69
WE	10.22	10.18	10.18	10.22	10.68	11.94	10.49	10.59	10.18
	3.78	3.77	3.77	3.78	3.99	3.74	4.03	3.95	3.77
kWh	Totals Gdata							Groups base	
WD	2.85	2.84	2.84	2.85	2.90	2.99	2.82	2.89	2.84
	0.99	0.99	0.99	0.99	0.97	0.96	0.96	0.99	0.99
WE	3.24	3.21	3.21	3.24	3.56	3.47	3.55	3.58	3.21
	1.13	1.12	1.12	1.13	1.19	1.12	1.20	1.23	1.12

Table C.1.10.6: Base, projections and groups for the coldest day average electricity demand per household and per person.

Coldest day									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2
WD	15.28	15.17	15.18	15.28	16.10	17.28	15.93	16.30	15.17
	5.66	5.61	5.62	5.66	6.02	5.41	6.11	6.09	5.61
WE	16.79	16.68	16.69	16.79	17.59	19.06	17.37	17.73	16.68
	6.22	6.17	6.18	6.22	6.58	5.97	6.67	6.62	6.17
kWh	Totals Gdata							Groups base	
WD	61.52	61.60	61.59	61.52	61.07	65.08	58.69	60.74	61.60
	21.46	21.52	21.52	21.46	20.40	20.97	19.90	20.82	21.52
WE	64.42	64.27	64.29	64.42	66.36	69.17	64.37	65.91	64.27
	22.47	22.46	22.46	22.47	22.17	22.29	21.83	22.59	22.46

Table C.1.10.7: Base, projections and groups for the comparing seasons daily average electricity and gas demand per household and per person.

Comparing season (Autumn 2009 (Edata) and Winter 2010-11 (Gdata))									
kWh	Totals Edata							Groups base	
	base	NSP	PR	MF	FW			G1	G2
					All	FWr	FWp		
AD	12.16	12.12	12.12	12.17	12.62	14.27	12.37	12.57	12.12
	4.50	4.48	4.49	4.50	4.71	4.47	4.75	4.69	4.48
WD	11.89	11.84	11.85	11.89	12.33	13.89	12.09	12.28	11.84
	4.40	4.38	4.38	4.40	4.60	4.35	4.64	4.58	4.38
WE	12.86	12.81	12.82	12.86	13.34	15.21	13.06	13.29	12.81
	4.76	4.74	4.74	4.76	4.98	4.76	5.01	4.96	4.74
kWh	Totals Gdata							Groups base	
AD	40.13	40.18	40.18	40.13	40.24	41.68	39.13	39.56	40.18
	13.99	14.04	14.04	14.00	13.45	13.43	13.27	13.56	14.04
WD	39.89	39.95	39.95	39.89	39.96	41.38	38.87	39.27	39.95
	13.91	13.96	13.96	13.91	13.35	13.33	13.18	13.46	13.96
WE	40.71	40.75	40.75	40.71	40.91	42.41	39.77	40.29	40.75
	14.20	14.24	14.23	14.20	13.67	13.67	13.49	13.81	14.24

C.1.11 Household size

The following tables are the projections of the daily average gas demand for the variable 'Household size' for winter, spring, summer, autumn, and the hottest and coldest days. They complement the projections from table 6.5.12.4.

Table C.1.11.1: Base, projections and groups for winter daily average electricity and gas demand per household and per person.

Winter													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5	G6
					All	FWr	FWp						
AD	14.30	15.63	14.04	13.46	16.36	15.02	16.55	9.23	12.73	15.45	17.65	20.55	22.25
	5.29	4.89	5.40	5.65	4.66	5.56	4.52	9.23	6.36	5.15	4.41	4.11	3.71
WD	14.08	15.39	13.82	13.25	16.10	14.74	16.30	9.11	12.54	15.23	17.32	20.23	21.89
	5.21	4.81	5.32	5.57	4.59	5.46	4.45	9.11	6.27	5.08	4.33	4.05	3.65
WE	14.84	16.24	14.57	13.96	16.98	15.72	17.17	9.55	13.20	15.97	18.44	21.34	23.14
	5.50	5.07	5.60	5.87	4.84	5.82	4.69	9.55	6.60	5.32	4.61	4.27	3.86
kWh	Totals Gdata							Groups base Gdata					
AD	43.39	44.96	43.20	42.47	45.17	43.96	45.01	34.20	42.74	44.45	46.02	49.86	52.86
	15.13	13.38	15.43	16.46	13.59	16.47	12.30	34.20	21.37	14.82	11.51	9.97	8.81
WD	43.01	44.60	42.82	42.09	44.76	43.36	44.68	33.71	42.39	44.07	45.72	49.30	52.87
	15.00	13.27	15.29	16.31	13.46	16.24	12.21	33.71	21.19	14.69	11.43	9.86	8.81
WE	44.31	45.85	44.14	43.42	46.17	45.46	45.81	35.42	43.59	45.40	46.78	51.25	52.85
	15.45	13.65	15.76	16.83	13.90	17.03	12.52	35.42	21.80	15.13	11.69	10.25	8.81

Table C.1.11.2: Base, projections and groups for spring daily average electricity and gas demand per household and per person.

Spring													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5	G6
					All	FWr	FWp						
AD	11.31	12.41	11.09	10.61	13.02	11.88	13.19	7.01	10.05	12.25	14.20	16.46	17.68
	4.19	3.88	4.27	4.46	3.71	4.40	3.60	7.01	5.03	4.08	3.55	3.29	2.95
WD	11.12	12.18	10.91	10.45	12.77	11.66	12.93	6.96	9.92	12.06	13.89	16.05	17.25
	4.12	3.81	4.20	4.39	3.64	4.32	3.53	6.96	4.96	4.02	3.47	3.21	2.87
WE	11.79	13.00	11.55	11.02	13.66	12.43	13.84	7.15	10.38	12.73	14.98	17.50	18.78
	4.37	4.06	4.44	4.63	3.89	4.60	3.78	7.15	5.19	4.24	3.74	3.50	3.13
kWh	Totals Gdata							Groups base Gdata					
AD	20.50	21.25	20.40	20.06	21.36	20.50	21.39	16.16	20.26	21.13	21.52	23.16	25.90
	7.15	6.32	7.29	7.78	6.42	7.68	5.85	16.16	10.13	7.04	5.38	4.63	4.32
WD	21.13	21.90	21.04	20.68	22.01	21.15	22.03	16.65	20.91	21.77	22.17	23.80	26.80
	7.37	6.52	7.51	8.02	6.61	7.92	6.02	16.65	10.46	7.26	5.54	4.76	4.47
WE	18.89	19.59	18.80	18.48	19.71	18.86	19.77	14.90	18.60	19.48	19.86	21.55	23.63
	6.59	5.83	6.71	7.16	5.92	7.06	5.40	14.90	9.30	6.49	4.96	4.31	3.94

Table C.1.11.3: Base, projections and groups for summer daily average electricity and gas demand per household and per person.

Summer													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5	G6
AD	10.32	11.32	10.13	9.71	11.91	10.75	12.08	6.20	9.34	11.28	12.99	14.89	15.70
	3.82	3.54	3.90	4.08	3.39	3.98	3.30	6.20	4.67	3.76	3.25	2.98	2.62
WD	10.21	11.20	10.01	9.59	11.79	10.62	11.96	6.13	9.19	11.16	12.84	14.77	15.65
	3.78	3.50	3.85	4.03	3.36	3.93	3.27	6.13	4.60	3.72	3.21	2.95	2.61
WE	10.63	11.62	10.43	10.01	12.22	11.08	12.39	6.38	9.71	11.59	13.35	15.21	15.81
	3.94	3.63	4.01	4.21	3.48	4.10	3.39	6.38	4.85	3.86	3.34	3.04	2.64
kWh	Totals Gdata							Groups base Gdata					
AD	3.58	3.69	3.57	3.53	3.75	3.58	3.76	2.85	3.56	3.94	3.63	3.79	4.26
	1.25	1.10	1.27	1.37	1.13	1.34	1.03	2.85	1.78	1.31	0.91	0.76	0.71
WD	3.62	3.73	3.61	3.56	3.79	3.60	3.81	2.86	3.59	3.98	3.67	3.84	4.34
	1.26	1.11	1.29	1.38	1.14	1.35	1.04	2.86	1.80	1.33	0.92	0.77	0.72
WE	3.49	3.58	3.48	3.44	3.65	3.52	3.65	2.80	3.48	3.82	3.53	3.68	4.07
	1.22	1.07	1.24	1.33	1.10	1.32	1.00	2.80	1.74	1.27	0.88	0.74	0.68

Table C.1.11.4: Base, projections and groups for autumn daily average electricity and gas demand per household and per person.

Autumn													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5	G6
AD	11.86	13.05	11.63	11.11	13.70	12.64	13.86	7.28	10.48	12.82	15.02	17.47	18.60
	4.39	4.08	4.47	4.67	3.90	4.68	3.79	7.28	5.24	4.27	3.76	3.49	3.10
WD	11.58	12.72	11.35	10.86	13.34	12.30	13.49	7.15	10.27	12.54	14.58	16.97	18.01
	4.29	3.97	4.37	4.56	3.80	4.55	3.69	7.15	5.13	4.18	3.65	3.39	3.00
WE	12.58	13.88	12.32	11.76	14.60	13.52	14.76	7.62	11.02	13.54	16.14	18.73	20.08
	4.66	4.34	4.74	4.94	4.16	5.01	4.03	7.62	5.51	4.51	4.03	3.75	3.35
kWh	Totals Gdata							Groups base Gdata					
AD	19.52	20.22	19.44	19.13	20.37	19.38	20.47	14.96	19.46	20.28	20.62	22.18	23.46
	6.81	6.02	6.94	7.41	6.11	7.26	5.59	14.96	9.73	6.76	5.15	4.44	3.91
WD	19.20	19.89	19.12	18.81	20.02	19.04	20.13	14.70	19.17	19.83	20.33	21.81	23.18
	6.70	5.92	6.83	7.29	6.01	7.13	5.50	14.70	9.59	6.61	5.08	4.36	3.86
WE	20.27	21.00	20.19	19.87	21.18	20.18	21.27	15.56	20.13	21.34	21.28	23.03	24.14
	7.07	6.25	7.21	7.70	6.36	7.56	5.81	15.56	10.07	7.11	5.32	4.61	4.02

Table C.1.11.5: Base, projections and groups for the hottest day average electricity demand per household and per person.

Hottest day													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5	G6
AD	9.97	10.96	9.78	9.36	11.49	10.33	11.66	5.94	8.91	10.92	12.72	14.52	15.24
	3.69	3.43	3.76	3.93	3.27	3.83	3.19	5.94	4.45	3.64	3.18	2.90	2.54
WD	10.22	11.23	10.02	9.61	11.77	10.88	11.91	6.05	9.16	11.26	13.21	14.21	15.99
	3.78	3.51	3.85	4.04	3.35	4.03	3.25	6.05	4.58	3.75	3.30	2.84	2.66
kWh	Totals Gdata							Groups base Gdata					
AD	2.85	2.98	2.83	2.77	3.04	2.91	3.04	2.04	2.82	2.91	3.06	3.39	3.76
	0.99	0.89	1.01	1.07	0.91	1.09	0.83	2.04	1.41	0.97	0.76	0.68	0.63
WD	3.24	3.38	3.22	3.17	3.41	3.33	3.39	2.51	3.08	3.47	3.52	3.55	4.26
	1.13	1.01	1.15	1.23	1.02	1.25	0.93	2.51	1.54	1.16	0.88	0.71	0.71

Table C.1.11.6: Base, projections and groups for the coldest day average electricity demand per household and per person.

Coldest day													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW All	FW FWr	FW FWp	G1	G2	G3	G4	G5	G6
AD	15.28	16.55	15.02	14.46	17.20	15.90	17.39	10.60	13.74	16.10	18.46	21.32	23.40
	5.66	5.17	5.78	6.07	4.90	5.89	4.75	10.60	6.87	5.37	4.61	4.26	3.90
WD	16.79	18.09	16.53	15.96	18.79	17.75	18.95	11.87	15.33	17.85	19.87	22.79	25.02
	6.22	5.65	6.36	6.71	5.36	6.57	5.18	11.87	7.66	5.95	4.97	4.56	4.17
kWh	Totals Gdata							Groups base Gdata					
AD	61.52	63.82	61.26	60.17	64.05	62.92	63.60	48.84	59.97	62.71	65.69	72.68	73.29
	21.46	18.99	21.88	23.32	19.28	23.57	17.38	48.84	29.98	20.90	16.42	14.54	12.22
WD	64.42	66.62	64.15	63.12	67.29	67.39	66.33	53.25	62.31	64.86	69.30	74.71	76.42
	22.47	19.83	22.91	24.47	20.30	25.24	18.12	53.25	31.16	21.62	17.33	14.94	12.74

Table C.1.11.7: Base, projections and groups for the comparing season daily average electricity and gas demand per household and per person.

Comparing season (Autumn 2009 (Edata) and Winter 2010-11 (Gdata))													
kWh	Totals Edata							Groups base Edata					
	base	NSP	PR	MF	FW			G1	G2	G3	G4	G5	G6
					All	FWr	FWp						
AD	12.16	13.40	11.92	11.39	14.05	12.93	14.22	7.33	10.78	13.34	15.34	17.78	19.33
	4.50	4.19	4.59	4.79	4.00	4.79	3.89	7.33	5.39	4.45	3.83	3.56	3.22
WD	11.89	13.07	11.65	11.15	13.70	12.62	13.86	7.22	10.57	13.06	14.93	17.24	18.71
	4.40	4.09	4.48	4.68	3.90	4.67	3.79	7.22	5.28	4.35	3.73	3.45	3.12
WE	12.86	14.22	12.59	12.01	14.94	13.73	15.12	7.62	11.31	14.03	16.34	19.12	20.90
	4.76	4.44	4.84	5.04	4.26	5.09	4.13	7.62	5.66	4.68	4.09	3.82	3.48
kWh	Totals Gdata							Groups base Gdata					
AD	40.13	41.42	39.98	39.35	41.66	40.23	41.63	32.50	39.82	40.93	41.69	46.31	47.92
	13.99	12.33	14.28	15.25	12.52	15.07	11.38	32.50	19.91	13.64	10.42	9.26	7.99
WD	39.89	41.19	39.74	39.11	41.38	39.87	41.40	32.24	39.57	40.67	41.54	45.95	47.88
	13.91	12.26	14.19	15.16	12.44	14.93	11.31	32.24	19.78	13.56	10.39	9.19	7.98
WE	40.71	41.99	40.57	39.94	42.33	41.12	42.22	33.15	40.45	41.58	42.04	47.22	48.01
	14.20	12.50	14.49	15.48	12.73	15.40	11.54	33.15	20.23	13.86	10.51	9.44	8.00

C.2 Other additions

C.2.1 Average month temperatures period 2009-2019

Table C.2.1.1 shows the average temperatures of each month in the weather station from Gurteen for the period 2009-2019. It also shows the average temperature of each month for the whole period (*e.g* the average temperature in May for the whole period), the standard deviation of the monthly temperatures in the period and the values for the average monthly temperature plus/minus the standard deviation. The range between these values is considered to be the "normal" range of temperatures for the month. Row 'Off' is a count of the number of Off-months in the year, *i.e.* the number of months in which the temperature was outside this normal range, and their average and standard deviations. The shadowed cells indicate months for which there is data available (Edata and/or Gdata). The bold faced values in these cells indicate average temperature outside the normal range of temperatures.

C.2.2 Appliance points explanation

The surveys for Edata contain a series of questions asking about appliances. These questions first ask for the number of specific appliances that the household owns and then it asks for how often they are used. A counting system has been set to classify the households based on how many appliances they own and how often they use them. Table C.2.2.1 shows a review of these questions, which column in the file 'Emetadata.m' (see Appendix

Table C.2.1.1: Average monthly temperatures in Gurteen's weather station (2009-2019).

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	mean	stdev	mean+ stdev	mean- stdev
Jan	4.2	**1.6**	3.0	6.6	4.9	5.2	4.7	5.7	5.9	5.5	5.6	4.8	1.4	6.2	3.4
Feb	4.9	**2.4**	**6.8**	7.0	4.5	5.4	4.2	4.6	6.0	3.4	7.5	5.2	1.5	6.7	3.7
Mar	6.9	5.0	6.0	8.1	3.3	6.6	5.9	5.9	7.8	4.5	6.9	6.1	1.4	7.4	4.7
Apr	8.7	8.4	**10.7**	6.5	6.9	9.6	8.1	6.9	8.4	8.5	8.9	8.3	1.2	9.5	7.2
May	10.7	10.2	10.7	10.6	9.9	11.4	9.8	11.9	12.0	12.0	10.7	10.9	0.8	11.7	10.1
Jun	14.4	14.6	11.6	13.1	13.1	14.3	12.8	14.5	14.3	15.7	12.6	13.7	1.1	14.8	12.6
Jul	14.5	15.3	14.1	14.1	17.5	16.3	13.9	15.4	15.0	16.9	16.2	15.4	1.2	16.5	14.2
Aug	14.8	**13.6**	13.0	15.6	15.2	14.0	13.9	15.3	14.2	15.2	15.3	14.6	0.8	15.4	13.7
Sep	12.4	13.4	13.4	11.9	13.2	14.0	11.9	13.8	12.4	11.8	12.9	12.8	0.8	13.6	12.1
Oct	11.1	9.5	11.3	8.3	11.6	10.9	10.2	10.0	11.0	9.3	8.9	10.2	1.0	11.2	9.2
Nov	7.1	**4.7**	9.6	5.8	5.9	7.0	8.8	5.1	6.8	7.3	5.6	6.7	1.4	8.1	5.3
Dec	**2.5**	**-0.4**	5.8	5.3	6.5	5.4	8.3	6.5	5.4	7.9	6.0	5.4	2.3	7.7	3.1
Off	11	7	4	4	7	10	7	8	10	5	9	7.5	2.3	–	–

Mean and stdev present the average and the standard deviation of the average temperatures of the particular month in the period 2009-2019. Mean+stdev and mean−stdev correspond to the the average temperature plus or minus the standard deviation.
Shadowed cells mark the months for which data (Edata or Gdata) is available, and bold face values mark those outside the normal range for the month.
Off stands for Off-months: the number of months for which the mean temperature is outside the range mean−stdev - mean+stdev.

D) shows the answer, and the points given to each answer. The total amount of points each household obtains is calculated by multiplying the points from 'Number of appliances' by 'How often' for each appliance and adding up all the results for the household.

There are 46 households which answered that they own an electric cooker but they did not answer for how long they use it (NaN in 'Emetadata.m' column 106). For all the other appliances the number of no-answers on questions about how long the appliance is used matches the number of households which answered that they don't own the given appliance. It is assumed that if no answer is given it is because the respondent could not recall using the appliance (only cookers here), therefore the lowest use time is assigned to them.

Table C.2.2.1: Column in Emetadata where the responses of each appliance question (number and how often is used) appears, and rubric of the points each question gives.

	Number of appliances	How often
Question number [unit]: rubric	Q49002: 1 = 0, 2 = 1, 3 = 2, 4 = >3	Q49004 [loads/day]: 1 = <1, 2 = 1, 3 = 2-3, 4 = 3+
Points	0, 1, 2, 3	1, 2, 3, 4
Washing machine	81	101
Tumble dryer	82	102
Dishwasher	83	103
Question number [unit]: rubric	(same Q number)	Q49000(0)4 [minutes used]: 1 = <5, 2 = 5-10, 3 = 10-20, 4 = >20
Points	0, 1, 2, 3	1, 2, 3, 4
Electric shower (instant)	84	104
Electric shower (electric pumped from hot tank)	85	105
Question number [unit]: rubric	(same Q number)	Q4900005-8 [hours used]: 1 = <0.5, 2 = 0.5-1, 3 = 1-2, 4 = >2
Points	0, 1, 2, 3	1, 2, 3, 4
Electric cooker	86	106
Electric heater (plug-in convector heaters)	87	107
A water pump or electric well pump or pressurised water system	89	108
Immersion	90	109
Question number [unit]: rubric	(same Q number)	Q4900009 1 = part of year (4-6 months), 2 = all year
Points	0, 1, 2, 3	2, 4
Stand alone freezer	88	110
Question number [unit]: rubric	Q490002: 1 = 0, 2 = 1, 3 = 2, 4 = 3, 5 = 4+	Q49022 [hours/day]: 1 = <1, 2 = 1-3, 3 = 3-5, 4 = >5
Points	0, 1, 2, 3, 4	1, 2, 3, 4
TV's less than 21 inch	96	111
TV's greater than 21 inch	97	112
Desk-top computers	98	113
Lap-top computers	99	114
Games consoles, such as xbox, playstation or Wii	100	115

Q stands for question.

Appendix D

Explanation of the electronic data provided

The electronic data provided with the thesis (file *Extra material - PhD thesis - Miquel Banchs-Piqué.zip*) is permanently stored with the DOI number 10.17029/29e32a09-fdd5-4171-9f26-28caf7abfe4e and can be openly accessed on-line in Pure. To do so, please click on the following link https://doi.org/10.17029/29e32a09-fdd5-4171-9f26-28caf7abfe4e or scan the QR code below.

This file contains the MATLAB code and arrays explained in Sections 6.3 and 7.2. In addition, an array with the results of projecting the data is included (*Allprojresults.mat*) to make it possible to directly use the function *aggregates.m*. It also contains the files with the CATI-coded questions asked in the pre-trial surveys for both, Edata and Gdata, for reference. These surveys, their answers and the energy data (CER, 2012a, 2012b) can be accessed via the ISSDA. And finally, a copy of the table of indicators developed by DRC (Lombardi et al., 2012) is also included for reference.

Figure D.0.0.1: Scan this QR code to access the electronic data that complements this thesis.

Appendix E

Ethics form

FORM UPR16

Research Ethics Review Checklist

Please include this completed form as an appendix to your thesis (see the Research Degrees Operational Handbook for more information

UNIVERSITY OF PORTSMOUTH

Postgraduate Research Student (PGRS) Information		**Student ID:**	UP8391
PGRS Name:	Miquel Banchs-Piqué		
Department:	SCES	**First Supervisor:**	Mark Gaterell
Start Date: (or progression date for Prof Doc students)		01/10/2016	
Study Mode and Route:	Part-time ☐ Full-time ☒	MPhil ☐ PhD ☒	MD ☐ Professional Doctorate ☐

Title of Thesis:	Projecting disaggregated household energy demand data into future scenarios: a tool to improve decision-making
Thesis Word Count: (excluding ancillary data)	82,300

If you are unsure about any of the following, please contact the local representative on your Faculty Ethics Committee for advice. Please note that it is your responsibility to follow the University's Ethics Policy and any relevant University, academic or professional guidelines in the conduct of your study

Although the Ethics Committee may have given your study a favourable opinion, the final responsibility for the ethical conduct of this work lies with the researcher(s).

UKRIO Finished Research Checklist:
(If you would like to know more about the checklist, please see your Faculty or Departmental Ethics Committee rep or see the online version of the full checklist at: http://www.ukrio.org/what-we-do/code-of-practice-for-research/)

a) Have all of your research and findings been reported accurately, honestly and within a reasonable time frame?	YES ☒ NO ☐
b) Have all contributions to knowledge been acknowledged?	YES ☒ NO ☐
c) Have you complied with all agreements relating to intellectual property, publication and authorship?	YES ☒ NO ☐
d) Has your research data been retained in a secure and accessible form and will it remain so for the required duration?	YES ☒ NO ☐
e) Does your research comply with all legal, ethical, and contractual requirements?	YES ☒ NO ☐

Candidate Statement:

I have considered the ethical dimensions of the above named research project, and have successfully obtained the necessary ethical approval(s)

Ethical review number(s) from Faculty Ethics Committee (or from NRES/SCREC):	ETHICS-10070

If you have *not* submitted your work for ethical review, and/or you have answered 'No' to one or more of questions a) to e), please explain below why this is so:

Signed *(PGRS)*:		**Date:** 29/07/2020

UPR16 – April 2018